Segregation, Spillovers, and the Locus of Racial Change

Donald R. Davis, Matthew Easton, and Stephan Thies*

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Abstract

Existing empirical research in economics on neighborhood racial sorting is overwhelmingly premised on the idea that racial preferences for a location depend on the racial shares in *that* location, without considering potential spatial spillover effects from nearby areas. Does this matter for the way we view the cross-section and dynamics of racial neighborhood segregation? We nest Schelling (1971)'s bounded neighborhood and spatial proximity theories within a discrete choice model, where the key distinction is precisely such spatial spillovers. We simulate the model and examine the data for 1970-2000 for more than 100 U.S. metros. Two features of the data are most compelling: the powerful presence of racial clusters and the fact that drastic racial change is concentrated at the boundary of these clusters. Both point to the spatial proximity model as the proper foundation for a theory of racial neighborhood evolution. We use these insights to revisit prominent results on racial tipping where our theory guides us to distinguish differences by location. While prior research pointed to powerful racial tipping in the form of White *exit*, we show this is largely driven by theoretically-distinct "biased white suburbanization" leading to White *entry* in remote areas. In urban areas far from existing Minority clusters, we find zero or small tipping effects, at odds with a bounded neighborhood interpretation. The most consistent effects of tipping, still of modest size, are found in areas adjacent to existing Minority clusters, confirming the relevance of the racial spillovers of the spatial proximity model. Existing research conflates these quite distinct effects. Overall, our results suggests that tipping is a less central feature of racial neighborhood change than suggested in prior research and that greater attention needs to be paid to spatial dimensions of the problem.

*Davis: Columbia University and NBER (email: drdavis@columbia.edu); Easton: Columbia University (email: me2713@columbia.edu); Thies: Columbia University (email: stephan.thies@columbia.edu). We are grateful to Leah Boustan, Rebecca Diamond, Jonathan Dingel, Ed Glaeser, Nina Harari, Stephan Heblich, Tomasz Michalski, Dan O'Flaherty, Giacomo Ponzetto, Allison Shertzer, and Daniel Sturm, as well as seminar and conference participants at Columbia University, Aalto University, INSEAD, Aix-Marseille University, London School of Economics, the Spring 2024 NYU-Columbia Trade Miniconference, the 7th IEB Workshop in Urban Economics, the 2024 European and North American Meetings of the Urban Economics Association, the 2024 North American and European Summer Meetings of the Econometric Society, the 2024 NBER Summer Institute, the Stanford SITE 2024 Housing meeting, and the Chicago-Princeton 2024 Spatial Conference. We thank Tommy Huang, Pablo Mones, and Luca Terzariol for excellent research assistance. We especially thank Iain Bamford and Howard Zhang for their contributions to earlier versions of the project. Easton acknowledges the Program for Economic Research at Columbia and the Alliance Doctoral Mobility Grant from Columbia and Sciences Po for support.

1 Introduction

Racial residential segregation is an enduring feature of American cities. Collective action, government intervention, and White flight all contributed to its rise (Boustan, 2010; Cutler et al., 1999; Rothstein, 2017; Shertzer and Walsh, 2019). While segregation began to decline in the aftermath of the landmark 1968 Fair Housing Act (Glaeser and Vigdor, 2012), discrimination in housing has not disappeared (Christensen and Timmins, 2022, 2023) and segregation persists at high levels (Logan and Stults, 2021).[1]

This racial division of our cities comes at high social cost. Recent research underscore the extent to which the neighborhoods we live in shape our life opportunities (Chyn and Katz, 2021). Randomized studies through the Moving to Opportunity program provide credible causal evidence of these effects (Chetty et al., 2016) and may be thought of as zero measure experiments in which the direction of causality runs from neighborhoods to outcomes for new residents. However, if we are ever to implement the implied interventions at scale, we will also need to understand the reverse direction, i.e. how new populations change neighborhoods (Derenoncourt, 2022).

In the United States, research on neighborhood change must confront the role of race and ethnicity (Boustan, 2016). The persistence of segregation suggests that drastic racial change need not only be of historical interest. This raises in turn the possibility that interventions to provide new access to good neighborhoods at scale could give rise to general equilibrium responses that partly or wholly undo the policy goals underlying the zero measure experiments. The dynamics matter.

Racial residential segregation is among the most highly studied topics in the social sciences, and so one might imagine that the cross-section and dynamics of segregation are well understood empirically and so could inform policy. This, however, is not the case. Consider the foundational theoretical work of Schelling (1971), which has in excess of 7,000 Google Scholar citations. Schelling developed there the bounded neighborhood and spatial proximity models. The first considers the fate of a single neighborhood and is the setting for articulating the highly influential tipping model. The second, often referred to as the checkerboard model, considers in an abstract setting an entire metropolitan community. Despite the broad academic success of Schelling's two models, they have received relatively little formal

[1] This is particularly true for the Black-White dissimilarity index, where fifteen of the fifty cities with the largest black populations, including *inter alia* New York, Chicago, Boston, and Philadelphia, remain in the range that Massey and Denton (1988) characterize as high discrimination more than a half century after the Fair Housing Act (Logan and Stults, 2021).

empirical scrutiny in economics. The presence of racial spatial spillovers, generic multiple equilibria, and discontinuities have stood as challenges that have made progress in formal empirics difficult.[2]

In this paper, we contribute to both the theory and empirics of residential segregation, considering both the cross section and dynamics. Our first contribution is to show how to nest variants of Schelling's bounded neighborhood and spatial proximity models in a common framework amenable to empirical examination. Our starting point is a stripped-down version of the static model of discrete neighborhood choice of Bayer et al. (2007). The bounded neighborhood model is characterized by the presence of *within-location spillovers*, so those choosing the location care about its racial composition. The contrast with the spatial proximity model is that the latter also allows for *cross-location spatial spillovers* in racial preferences. We first develop the partial equilibrium of our discrete choice bounded neighborhood model to highlight features that link our approach to the correlate in Card et al. (2008a). We then provide an explicit nesting of general equilibrium versions of the bounded neighborhood and spatial proximity models.

We use the nested models as a foundation for simulations that develop contrasting empirical implications of the models, which vary according to the absence (bounded neighborhood) or presence (spatial proximity) of spatial racial spillovers. Two contrasts are fundamental. The first of these is the salience of racial clusters. The bounded neighborhood model, lacking spatial spillovers across locations, implies that such clusters arise only randomly. The spatial proximity model says these clusters will instead be a first-order feature of the world. The second salient contrast is the locus of racial change. Again, the bounded neighborhood model provides guidance about evolution within a tract, but it doesn't provide any guidance about where change will happen relative to existing tracts of varied types. By contrast, the spatial proximity model predicts that racial neighborhood change will occur at the boundary of existing racial clusters. In this setting, the cross-section and dynamics are of a piece, where the spatial nature of the dynamics focused on boundaries preserves the existence of racial clusters.

We also develop two additional cross-sectional predictions of the models concerning the behavior of the Minority share and housing prices at the boundary of racial clusters. The absence of cross-location racial spillovers in the bounded neighborhood model predicts discrete jumps in both Minority share and housing prices at the boundary of racial clusters,

[2]The fact that Schelling, a future winner of the Nobel Prize in Economics, published this seminal paper in the *Journal of Mathematical Sociology* rather than a top-tier economics journal indicates the methodological challenges economics has faced in grappling with his ideas.

while the spatial proximity model predicts strong but non-precipitous gradients at these locations. Asymmetries in the strength of racial homophily also have observable consequences in the spatial proximity model that contrast with those in the bounded neighborhood model. When homophily preferences of Minorities are weak and those of Whites are strong, the spatial proximity model predicts that housing prices vary little inside the Minority cluster but rise strongly as we move from the boundary to the interior of the White cluster. In the bounded neighborhood model, this would also yield higher prices for Whites, but these would have a discrete jump at the boundary of clusters and have little variation internal to either cluster. These four contrasting predictions of the models allow us to discriminate between them.

A key feature of our model is the presence of multiple equilibria when racial preferences are sufficiently strong and extend beyond the boundaries of a tract. To summarize predictions of our model in a way that is robust to hysteresis and to investigate our hypotheses empirically, we reduce the dimensionality of the U.S. census tract data in a new way. We first operationalize the idea of clustering by considering sets of N (varying) or more contiguous census tracts with the same racial mode as a cluster. This permits us to investigate the salience of clusters in the racial geography of U.S. metro areas, an aspect that standard measures of segregation such as the dissimilarity or isolation indices cannot capture. We then develop a novel way of visualizing the data. We focus on the distance in units of tracts of a location from a cluster boundary, i.e., a border where two tracts of different modal race abut. These visualizations allow us to examine key contrasts in the interior versus the edge of racial clusters, both in the cross section and across decades.

We examine the contrasting predictions between the two general equilibrium models empirically using U.S. Census data from 1970 to 2000 for over 100 metropolitan statistical areas (MSAs). The results of this examination strongly support the spatial proximity model. Racial clusters are a first-order feature of American cities. Change in racial composition is strongly concentrated at the boundary of clusters. Minority shares have a non-precipitous change at the boundary of clusters. Our predictions for housing prices confirm both that there is a non-precipitous gradient at the boundary of racial clusters and that there is a contrast in the behavior of the prices internal to clusters consistent with an asymmetric degree of homophily preferences.

Our results strongly support the spatial proximity model. However, the bounded neighborhood model is the foundation for nearly all existing empirical work on segregation in economics. For example, in its partial equilibrium form, it is the framework within which the “tipping” empirics of Card et al. (2008a) is developed. In its general equilibrium form, following Bayer et al. (2007), it is the setting for nearly all empirics that consider race as a factor in neighborhood choice.

Does the strong reliance of the existing empirical literature in economics on variants of the bounded neighborhood model matter crucially for their results? We do not think there can be an *a priori* uniform answer. Context matters and in particular investigations this neglect may be of little consequence. That said, a fundamental point of Schelling’s spatial proximity model is that even racial preferences that are far from extreme and that have limited direct spatial scope can have large macro-spatial consequences. And the results favoring the spatial proximity model are not subtle. Our findings thus highlight the high returns to examining the extent to which these spatial racial spillovers matter in each context.

In this spirit, we use the insights from our work above to revisit core results from the classic paper of Card et al. (2008a). That paper is firmly rooted in the partial equilibrium bounded neighborhood model and develops a framework for the empirical estimation of metro-specific neighborhood tipping points in more than 100 U.S. MSAs. The influence of the paper has been powerful in large measure because of its surprising result finding large discontinuities of White neighborhood exit as soon as the Minority share of a census tract exceeds a metro-specific tipping point.

Spatial racial spillovers are central to our spatial proximity approach and absent from their bounded neighborhood approach. As a result, space, and especially distance from the boundary of racial clusters, is central for us and primarily the subject of robustness checks for them. These contrasts lead us to opposite conclusions about the relevant racial dynamics. Card et al. argue strongly against what they term the “expanding ghetto model.”[3] Indeed they claim that tipping is strongest in areas remote from the existing Minority clusters. To see why we end up with results in such apparent tension, we first re-examine their results and identify elements that seem problematic. We then go on to develop what, in light of our theory, seems a more appealing spatial approach.

Since the heart of the tension between the work of Card et al. and ours is the role of space, one wants to look not only at sample statistics, plots, and regressions, but also at maps. This is clearly not feasible for over 100 MSAs in the sample and across four censuses. So, as a heuristic, we first investigate the case of Chicago in 1970-1980, whose experience stood

[3]They attribute the “expanding ghetto model” to Möbius and Rosenblat (2001). But, as suggested above, racial change happening at the boundary of clusters is a property of Schelling’s spatial proximity model, which our empirics endorse.

out as an extremely powerful example of tipping in their analysis. Card et al. identify a tipping point between 1970 to 1980 in Chicago at a tract's Minority share of 5.7%. Moving beyond this tipping point leads to a discontinuous drop of roughly 30 percentage points in White population growth in that decade.

A closer look at the data for Chicago 1970-1980 suggests a different story. Unbinning and then mapping the data indeed confirms that the process of racial neighborhood change is deeply spatial. The process in urban neighborhoods is radically different from that in suburban neighborhoods, where the first is driven by White *exit* and the second by White *entry*. Likewise the processes are different in urban neighborhoods near or far from the boundary of racial clusters, where drastic White exit is concentrated in the former. Card et al.'s headline results pool these changes, hence conflate quite distinct social processes.

To extend the insights that we gain from the case study of Chicago across all MSAs, we develop a spatially stratified approach, building on the methodology of Card et al.. We test, using changes in levels of the White, Minority, and total population as our dependent variables, for the significance of tipping discontinuities in suburban tracts as well as in urban tracts close to and remote from the boundary of a Minority cluster. The contrast in results between urban areas more- versus less-exposed to the boundary of racial clusters can be thought of as a contrast between the spatial proximity model, which says this exposure should be crucial, and the bounded neighborhood model, which says that, beyond the initial Minority share of a tract, exposure to proximate neighborhoods should not matter. The regressions for the suburban areas, where White entry drives differences, may be thought of as a test of "biased White suburbanization." These draw on the ideas that the arrival of Minorities to central cities may have a causal impact on White exit (Boustan, 2010) and that such relocation may feature "White avoidance" of mixed race areas (Ellen, 2000).[4]

The spatially stratified results for all MSAs make a number of central points. The first is that the measured tipping discontinuities from these regressions are a poor guide to where drastic racial change is actually occurring. For example, looking at 1970-1980 for all MSAs, the measured tipping magnitude for urban tracts more exposed to Minority clusters is only half that estimated for suburban tracts. Yet the likelihood of drastic White exit of 25 percentage points or more in the more-exposed urban tracts is over six times as large as in suburban tracts. Second, the tipping coefficients for each of the spatial areas reveal that the powerful measured tipping effects in suburban areas in the first two decades are all about White entry that veers away from existing concentrations of Minorities. This is a racial story, but not of

[4] In the period we study, this may have been accelerated by the construction of interstate highways (Baum-Snow, 2007; Weiwu, 2023).

White exit and tipping. The less-exposed urban areas that should be the purest test of the bounded neighborhood model show statistically zero tipping effects in the first two decades and small ones in the third. Finally, we do see some economically meaningful tipping effects in the urban more-exposed areas. But these tipping discontinuities average only about 5 percent across the three decades even though these areas are the very center of drastic racial change. It is hard to conclude that the tipping discontinuity is really a central part of understanding the drastic racial change. An additional analysis using decadal changes in the White *share* as our dependent variable reinforces these findings.

We have a few bottom lines. Our nesting of the spatial proximity and bounded neighborhood models to understand segregation turns on the presence of spatial racial spillovers. Our data exercise on over 100 MSAs across four censuses strongly supports the spatial proximity model, hence the importance of these spillovers. Most importantly, this is due to the salience of spatial racial clusters and the locus of racial change being at the boundary of these clusters. Since nearly all existing empirical work on segregation in economics is tied to the poorly performing bounded neighborhood model, it is important that future work consider the role of these spillovers. As a start, we re-examine the prominent results of Card et al. (2008a), which have a number of points of tension with our work. We find that their headline tipping results conflate very different social processes in suburban areas as well as urban areas less- and more-exposed to Minority clusters. Overall, measured tipping through the approach of Card et al. (2008a) seems at most of very modest importance in the larger process of drastic racial change that characterized these periods.

Relation to the literature

Our work contributes to several strands of literature addressing racial segregation, neighborhood sorting, and the broader dynamics of urban change.

Foundational theoretical works are Schelling (1969, 1971); Becker and Murphy (2000); Brock and Durlauf (2001); Sethi and Somanathan (2004). A significant strand of the literature consists of simulated agent-based models, including Zhang (2004, 2011) and Axtell and Farmer (2022). We add to this literature by nesting Schelling's bounded neighborhood (including tipping) and spatial proximity (checkerboard) models in a common discrete choice framework amenable to empirical investigation.[5]

Massey and Denton (1988) provide an overview of measures to quantify segregation, including

[5] Work on racial segregation which influenced the early economics literature include Franklin (1956) and Grodzins (1957)

the dissimilarity and isolation indices. Echenique and Fryer Jr (2007) and Harari (2024) refine these measures to account in different ways for space, although without the focus on racial clusters and the boundaries between them central to our work. Dai and Schiff (2023) provide a way to operationalize the idea of ethnic clusters, but not in a way appropriate to our efforts. We instead partition tracts into clusters defined as groups of contiguous tracts with the same racial mode, allowing us to focus on how neighborhood racial change occurs distinctly according to a location's distance to the boundaries of these racial clusters.

Empirical investigations into the patterns and causes of racial residential segregation in the U.S. can be found in Cutler et al. (1999); Ellen (2000); Card et al. (2008b); Glaeser and Vigdor (2012); Boustan (2016); Logan and Parman (2017); Shertzer and Walsh (2019); Logan and Stults (2021). Work with a focus variously on the interplay between segregation, the great migration, and suburbanization appears in Baum-Snow (2007); Boustan (2010); Weiwu (2023); Bagagli (2023); Neubauer and Fabian (2024). There is a focus on neighborhood racial tipping in Easterly (2009) and Card et al. (2008a,b). We add to this literature by introducing a theoretically well-grounded approach to empirical examining the role of the spatial proximity of racial groups in neighborhood evolution.

More recent empirical investigations into neighborhood sorting by race and class heavily rely on discrete choice models that can capture general equilibrium effects. This literature includes Bayer and Timmins (2005, 2007); Bayer et al. (2007, 2014); Caetano and Maheshri (2017); Almagro et al. (2023); Tsivanidis (2023); Blair (2023); Weiwu (2023); Couture et al. (2023); Li (2023); Couture et al. (2024) using static models and Bayer et al. (2016); Caetano and Maheshri (2023); Davis et al. (2023) using dynamic models. We extend this literature by incorporating spatial racial preferences and studying their consequences on the city-level. The papers most similar to ours in the focus on social spillovers across space are Redding and Sturm (2024) and Bagagli (2023). The former focuses on sorting by socioeconomic status in London and the latter estimates spatial racial preferences in the context of expressway construction in Chicago. We investigate the implications of spatial racial spillovers for racial clustering and the locus of drastic racial change in all US metros from 1970 until 2000.

Outline

The remainder of the paper is structured as follows. Section 2 introduces our model of discrete neighborhood choice with spatial spillovers. It also examines how the model nests Schelling's ideas of tipping, explains our simulation procedure, and introduces our main empirical hypotheses. In the following Section 3 we assess our hypotheses empirically. In light of our findings, Section 4 revisits results by Card et al. (2008a), and Section 5 concludes.

2 A Model of Neighborhood Choice and Spatial Spillovers

The theoretical ideas of Schelling (1971) are transparent, enormously influential, and yet difficult to take to data. For this reason, formal empirical work in economics based on his models ranges from sparse (bounded neighborhood and tipping models) to non-existent (spatial proximity and checkerboard model).[6] In this section, we will show that many of Schelling's main ideas can be introduced into a common framework that nests them in a discrete choice model, which allows us to create a set of predictions we can investigate with data.

2.1 A Discrete Choice Model with Spatial Spillovers

We start by describing the overarching model and its general parametrization before contrasting the main predictions of its bounded neighborhood and spatial proximity versions in the next section. The model has the following components.

Geography Space consists of a discrete set of locations $j \in J$ endowed with a distance metric d_{jk} that describes the distance between two locations j and k. In our empirical analyses we will focus on census tracts.

Demand There are different population groups $r \in R$ living in the city each having an exogenous total size of N_r. The total population inhabiting the city is thus $N = \sum_{r \in R} N_r$. Following a simple logit specification, households i of group $r(i)$ derive the following indirect utility from living in j

$$v_{ij} = u_{r(i)j} + \epsilon_{ji} \tag{1}$$

where ϵ_{ji} is a household- and location-specific i.i.d. Gumbel shock with unit scale. The location-specific mean utility is common across groups and takes the following form

$$u_{r(i)j} = -\alpha_{r(i)} \log(p_j) + \beta'_{r(i)} \sum_{k \in J} w_{jk} s_k + \eta_{r(i)j}. \tag{2}$$

Here, p_j is the average rental price of housing at location j and $s'_k = (s_{1k}, \ldots, s_{Rk})$ is a vector of neighborhood group shares at location k. Neighborhood fundamentals and amenities which do not endogenously respond to racial sorting but which can be group-specific are

[6] Schelling (1971) is considered one of the founders of agent-based modeling and there is a large literature based on this foundation (Axtell and Farmer, 2022). The only formal empirical work in economics we are aware of that explicitly takes as its setting the spatial proximity model is the very interesting, but apparently abandoned, project by Möbius and Rosenblat (2001). The recent work by Bagagli (2023) has some related elements.

captured through η_{rj}. The scalar α_r describes the price sensitivity and the vector $\beta_r' = (\beta_{r1}, \ldots, \beta_{rR})$ captures the racial preferences of group r for all other racial groups.[7] To gain intuition, the baseline formulation of our model features racial preferences that enter indirect utility linearly but the setup can in principle be extended to more complex cases.[8]

The key distinction between our model and most existing discrete choice models of segregation is the incorporation of spatial spillovers in racial preferences through the origin-destination-specific weights w_{jk}. The inclusion of these weights allows us to bridge the gap between Schelling's spatial proximity and bounded neighborhood models. The weights describe the degree to which households living at j care about the racial composition in location k. In principle, the distance decay could have an arbitrary form varying by race and depending on population density or the local transportation network. In our core model, we assume that w_{jk} decays exponentially with distance, where the decay rate is determined by κ, and weights satisfy the normalization $\sum_k w_{jk} = 1$:

$$w_{jk}(\kappa) = \frac{e^{-\kappa d_{jk}}}{\sum_{k' \in J} e^{-\kappa d_{jk'}}}$$

Using this formulation, racial preferences are very localized if $\kappa \to \infty$, meaning that households only care about the racial composition at location j itself. By contrast, only the city-wide racial composition plays a role if $\kappa = 0$.

Households choose where to live by maximizing their utility. This yields the following aggregate demand of group r for location j depending on the vector of all prices, neighborhood racial shares, and exogenous demand shifters:

$$D_{rj}(\{p_k\}, \{s_k\}, \{\eta_{rk}\}) = N_r \frac{\exp(u_{rj})}{\sum_{k \in J} \exp(u_{rk})} \tag{3}$$

Supply In the baseline version of our model, supply for housing is fixed and exogenous. Each location is endowed with a fixed housing stock H_j and total housing units available

[7] Racial preferences here should be interpreted broadly. While the parameter vector β_r can capture direct preferences for the race of neighbors, it also captures preferences for all neighborhood attributes that vary endogenously as the racial composition of the neighborhood changes.

[8] Note that this indirect utility formulation can also be derived by assuming a Cobb Douglas utility function with a housing share of $\tilde{\alpha}_r$ and a multiplicative taste draw that is i.i.d. Fréchet distributed across locations with shape parameter $1/\sigma_r$, location parameter 0, and scale parameter 1. The log indirect utility in this formulation would be equivalent to our additive formulation in Equations (1) and (2) with our price sensitivity α_r corresponding to the housing share multiplied with the shape parameter $\alpha_r = \tilde{\alpha}_r/\sigma_r$.

equal the total population: $\sum_{j\in J} H_j = N$.[9]

Equilibrium The share s_{rj} of group r at location j is given by

$$s_{rj} = \frac{D_{rj}(\{p_k\},\{s_k\},\{\eta_{rk}\})}{\sum_{r'} D_{r'j}(\{p_k\},\{s_k\},\{\eta_{rk}\})} \tag{4}$$

An equilibrium is then defined by a vector of prices $\{p_k\}$ and a matrix of racial shares $\{s_{rk}\}$ such that Equation 4 is satisfied and housing supply equals total demand at each location

$$H_j = \sum_r D_{rj}(\{p_k\},\{s_k\},\{\eta_{rk}\}). \tag{5}$$

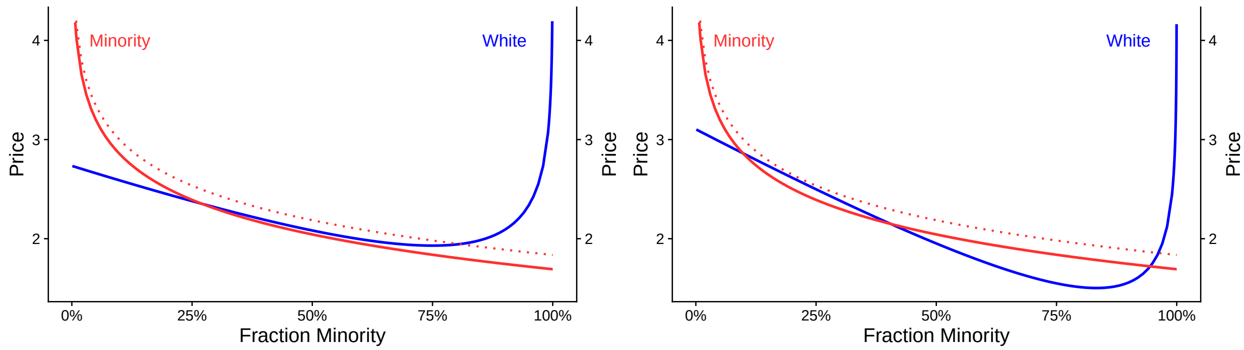
The existence of an equilibrium can be shown through Brouwer's fixed point theorem but uniqueness is not guaranteed (Bayer and Timmins, 2005). In fact, multiple equilibria are a key feature of the model and arise if agglomeration forces in the form of racial preferences and spillovers are sufficiently strong.

Simplifying assumptions In all of the following we will focus on two racial groups $R = \{w, m\}$ where w indicates White and m indicates Minority households.[10] Since racial preferences enter linearly in the baseline version of our model and there are only two racial groups, we can describe the racial composition of location k by its scalar Minority share s_{mk}. This also implies that racial preferences of each group can be fully described by the scalars β_{ww} and β_{mm} i.e. the preference of Whites for living with Whites (and thus not with Minorities) and the preference of Minorities to colocate with other Minorities (and thus not with Whites). For ease of notation, we will refer to these simply as β_w and β_m, respectively. We limit ourselves to this simplified two-group analysis, as much of the existing literature on tipping is written in a two-group context and the simplified setting allows us to gain intuition more easily.[11] As the general model foreshadows, most of what follows can be extended to a multi-group setting.

[9] The model can easily be extended to allow for endogenous supply for example by specifying a simple reduced form housing supply curve such as $H_j = \bar{H}_j p_j^{\theta_j}$ where $\bar{H}_j$ is a supply shifter and θ_j is the local supply elasticity.

[10] We take non-Hispanic White individuals to be "White", and all other races and ethnicities to be "Minority". The two groups defined here, in our theoretical portion, align with definitions of racial groups we use for analysis in our empirical section.

[11] For example Schelling (1969, 1971); Becker and Murphy (2000); Card et al. (2008a) and Easterly (2009) all consider a two group context. Recently Caetano and Maheshri (2017) have explored multi-group tipping in a school choice setting.



(a) Moderate homophily with unique equilibrium **(b)** Strong homophily with multiple equilibria, tipping

Figure 1: Bid-Rent Curves for Different Homophily Preferences

2.2 Nesting Existing Models

The theoretical model outlined above can nest the key aspects of the existing literature on racial neighborhood tipping. To see this more clearly we will consider three versions of our model: (1) a partial equilibrium version; (2) a general equilibrium version without spatial spillovers; and (3) a general equilibrium version with spatial spillovers.

The foundational theoretical work on neighborhood tipping is by Schelling (1969, 1971). Becker and Murphy (2000) show how to convert this to a more conventional partial equilibrium setting. Card et al. (2008a) introduce tipping in the latter framework and, along with Easterly (2009), develop related empirical work. Focusing on a discrete location, a bid-rent function describes the maximum willingness to pay of a marginal household to move into the location given a certain Minority share at that location. Our model allows for the derivation of graphical bid-rent functions when focusing on a single location, assuming that housing supply is inelastic, and when abstracting from general equilibrium adjustments.[12]

Two cases of bid-rent functions are provided in Figure 1, which we will use to illustrate the central insights derived from the partial equilibrium approach. The bid-rent curves for Whites are colored blue, while those for Minorities are colored red. The dotted lines show how the Minority bid-rent curve shifts outward in response to an increased Minority demand for the location, for example due to an aggregate inflow of Minorities into the city. Panel (a) illustrates a setting with moderate homophily preferences of Whites, zero racial preferences of Minorities, and a unique partial equilibrium. Panel (b) shows a setting with strong homophily preferences of Whites in which multiple equilibria exist. The difference in shape of the bid-rent functions across the two panels emphasizes a characteristic feature of

[12] For details on the derivation, see Appendix B

homophily in the model. For Minority households, who are assumed to have zero homophily preference here, the bid-rent function has the conventional downward sloping shape. For White households, the bid-rent function first becomes more elastic and later upward sloping as the strength of homophily preferences increases.

In both Panels (a) and (b), upward shifts of the Minority bid-rent function can lead to drastic changes in equilibrium Minority shares, and in both panels these changes are associated with reductions in neighborhood prices. With moderate homophily preferences adjustments occur without involving a bifurcation or crossing of a proper tipping point. In Panel (b), an upward shift of the Minority bid-rent curve can render the low Minority share equilibrium unstable. It is the existence of such bifurcations that is commonly understood as a central element in the theory of tipping. However the fact that drastic racial change in the partial equilibrium framework is possible both when a formal bifurcation exists (Panel b) and when it does not (Panel a) is a caution that drastic change alone is not evidence of such bifurcations. It also suggests the potential value of considering such drastic change directly as tipping without only or necessarily focusing on a search for bifurcations.[13]

The partial equilibrium model provides a rich setting for contemplating the fate of a single neighborhood in response to shocks. However the shortcomings of the framework are clear, particularly when we consider the evolution of all census tracts within a city. The aggregate shock contemplated, that of an upward movement in the Minority bid-rent curve, leads to White *exit* from the neighborhood. This is true whether or not tipping in the form of a bifurcation is formally present. When we try to apply this to understanding what happens for all tracts in an MSA, it is clear that one must move to general equilibrium in order to understand the adding-up constraints that affect White *entry* to other neighborhoods. Everyone must go somewhere.[14] In addition, the partial equilibrium approach has no clear predictions about the spatial location of neighborhood racial change. It does not provide a setting that allows us to understand how shifts in bid-rent functions will differ by location and whether we should expect the importance of tipping to vary across space.

To move beyond partial equilibrium and a single neighborhood, we can invoke the full equilibrium structure of our model. With $\kappa \to \infty$ we abstract from spatial spillovers in racial

[13]Our approach to the bounded neighborhood model has similarities and contrasts with the model developed by Card et al. (2008a). The model does admit the possibility of a tipping point at a critical Minority share s^*_{mj}. However one feature of the logit demand model relevant here is that the bid-rent curve of group r will always tend to infinity for low values of s_{rj}. This ensures that in every location households from every group are represented in expectation. In the post-tipping equilibrium, the Minority share won't be strictly $s_{mj} = 1$, which is in any case rare in the data.

[14]This will prove important when we seek to understand the roles, respectively, of White exit and White entry in driving prominent empirical results in the partial equilibrium model in Card et al. (2008a).

preferences and move to the general equilibrium bounded neighborhood model. This version alleviates concerns about adding-up constraints, which will be met when satisfying the general equilibrium conditions in Equations (4) and (5). The flexible structure of the demand function with exogenous location- and race-specific demand shifters η_{rj} allows the model to be taken to the data and can match observed heterogeneity in prices as well as the distribution of racial groups across locations in a city. Due to this flexibility, most of the recent quantitative urban literature on racial sorting works with a model that is conceptually close to our bounded neighborhood formulation (Bayer et al., 2007; Almagro et al., 2023; Weiwu, 2023).

An important tension remains in both the partial and general equilibrium bounded neighborhood model. The central point of these models is that households have strong preferences about the racial composition of their neighborhood. For this reason, it seems implausible that preferences stop at the often arbitrary boundaries of the census tracts used to examine these models empirically. The bounded neighborhood model does not allow for these spillovers across neighborhoods, while the spatial proximity model with $\kappa < \infty$ makes them a key element of analysis.

One of Schelling's central insights was that micro-motives responding to localized spillovers can have important macro consequences. However, few empirical papers model these spillovers, as estimation can be challenging. Bagagli (2023) is to our knowledge the first empirical paper in economics focusing on these cross-location racial spillovers in her study of the sorting consequences of expressway construction in Chicago. Redding and Sturm (2024) also estimate a spatial proximity model, while focused on spillovers due to socioeconomic status in London rather than race.

In what follows, we take a distinct approach. Instead of estimating the bounded neighborhood and spatial proximity models, we simulate the two and contrast key differences in their predictions. In Section 3, we then turn to data from a panel of US cities to examine the key patterns that help to distinguish the two models.

2.3 Simulating the Bounded Neighborhood and Spatial Proximity Models

In this section we simulate the bounded neighborhood and spatial proximity models to develop a set of empirical features we can examine with data. We have to make a range of decisions regarding parameters, spatial resolution, and initializations to simulate the models. In the following, we focus on simple cases illustrating the key predictions that the spatial proximity model makes but that the bounded neighborhood model cannot explain endogenously.

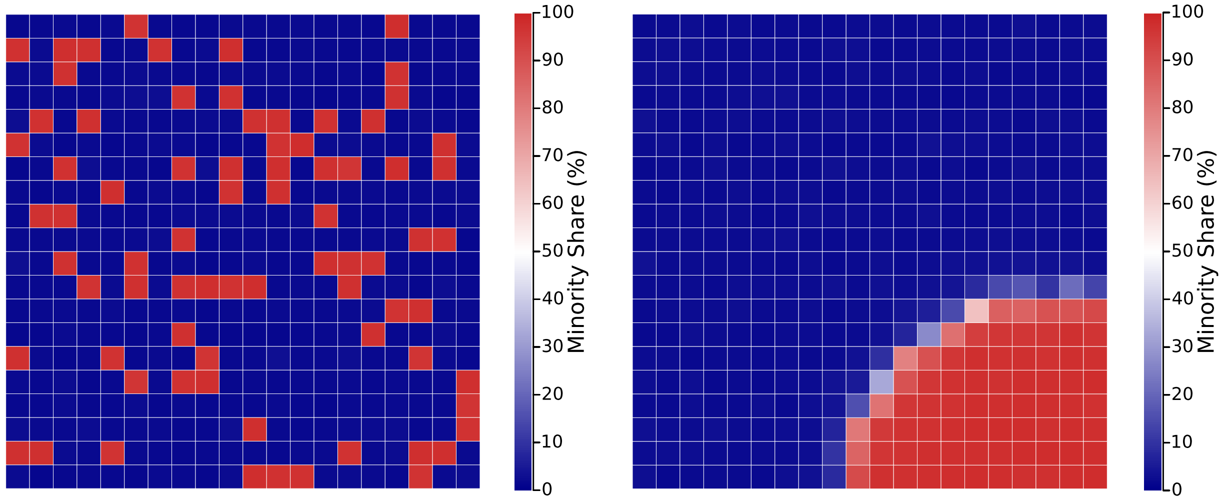
We simulate rectangular cities with 400 locations arranged on a 20×20 unit grid. Each location has fixed and identical housing supply. Demand comes from a unit mass of households. At baseline, 80% of households are White and 20% of households belong to the Minority group. Each group has equal price sensitivity $\alpha_m = \alpha_w = 10$ and Whites have strong homophily preferences ($\beta_w = 8$) while Minorities are indifferent about the racial composition of their neighborhood ($\beta_m = 0$).[15] The chosen parameters imply a semi-elasticity of $\beta_w/\alpha_w = 8/10 = 0.8$, i.e. if the average Minority share in the neighborhood increases by 1 percentage point, prices must decrease by 0.8% to keep White households indifferent.

We set fundamentals η_{rj} close to zero in all simulations so that there are no important exogenous reasons why demand of each racial group should vary across locations. This allows us to focus on the endogenous patterns that each model generates.[16] To find an equilibrium, we initialize each location with a Minority share s_j^0 that is independently drawn from a uniform distribution. Given the initial Minority shares $\{s_j^0\}$ we find the price vector $\{p_j^0\}$ that balances supply and demand at each location. Given this price vector, we can compute demand of each racial group for each location and update Minority shares respectively. We then iterate between updating prices and Minority shares until we converge to an equilibrium satisfying Equations 4 and 5.

Figure 2 contrasts equilibrium Minority shares arising after the *same* random initialization of the model in the bounded neighborhood version (Panel a) and in the spatial proximity version (Panel b). The bounded neighborhood version assumes $\kappa \to \infty$, so spatial racial spillovers are zero. The spatial proximity version features spillovers with $\kappa = 35$. Together with our assumption of locations on a unit square, this implies that in the spatial proximity version the racial composition of a location itself contributes on average about 45%, the 8 neighboring tracts together contribute 28%, and all other tracts combined contribute the remaining 27% to the experienced racial composition at a location. The equilibrium Minority shares in Panel (a) directly reflect the random initialization of the model. By contrast, Panel (b) shows a remarkable amount of clustering, even though it derives from exactly the same initialization. This highlights the first key feature, that the spatial proximity model endogenously delivers

[15] Weiwu (2023) provides support for the contrast of strong homophily preferences for Whites and (in her exercise) zero homophily preferences for Blacks.

[16] Across racial groups and locations, we do allow for a negligible shock on η_{rj} that is drawn independently and identically from a Normal distribution with a standard deviation of 0.1. These small shocks help in breaking ties in our convergence routine. Ties can occur when the numerical equilibrium solver converges towards an unstable equilibrium. In these situations a random neighborhood needs to tip and the algorithm cannot determine which location this should be as all neighborhoods appear identical in fundamentals. In such cases, the small iid shocks on η_{rj} help to determine which neighborhood will tip.



(a) Bounded Neighborhood

(b) Spatial Proximity

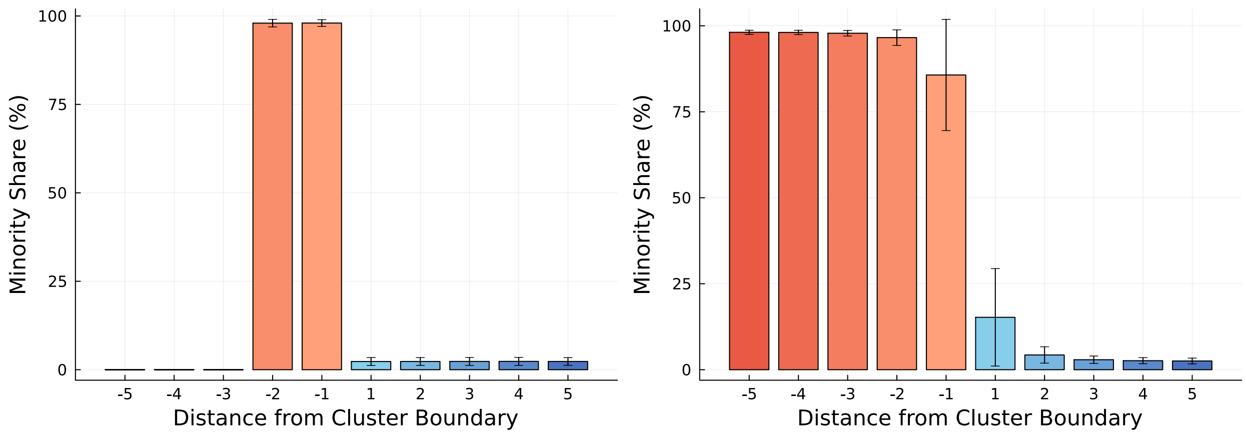
Figure 2: Racial Clustering in General Equilibrium Simulations

the formation of Minority clusters.

While one can easily spot the stark difference in the amount of clustering between the bounded neighborhood and spatial proximity models in Figure 2, we require a quantitative measure of clustering when running repeated simulations and when turning to census data in the next section. We define a racial cluster as a set of n contiguous locations with the same modal race. For any threshold n, we can then calculate the fraction of households living in own-race clusters.[17]

Having defined clusters, we need to resolve another issue for visualizing repeated simulations and census data: Due to strong homophily preferences, multiple equilibria are a common feature of this setting. To visualize the key spatial patterns in a manner that is robust to the existence of multiple equilibria and comparable across geographies, we proceed in the following way: We assign an integer distance to each location that reflects the minimum number of tracts one has to traverse to reach the border between clusters of opposite mode. Thinking of the boundary itself as location 0, we assign negative integers to locations that

[17]There is a considerable amount of work on clustering across many fields. Much of this focuses on the construction of scalar measures of the degree of clustering. This is not adequate to our needs, since we need to be able to locate clusters in physical space and to measure the location of tracts relative to the boundaries of these clusters. We thus take the definition of clusters as primary and then measure the degree of clustering according to the fractions of group populations living in same-mode clusters. In related work, Dai and Schiff (2023) provide an interesting method for constructing ethnic clusters using US census data. Our approach, based on the modal race, is better suited to our problem since it provides a unique mapping of every census tract to one of our two groups.



(a) Bounded Neighborhood **(b)** Spatial Proximity

Figure 3: Mean Minority Shares by Distance from the Cluster Boundary

Notes: Bar plots show averages across 1000 different initializations. Observations with an absolute distance from the cluster boundary larger than 5 are dropped to focus on patterns close to the cluster boundary.

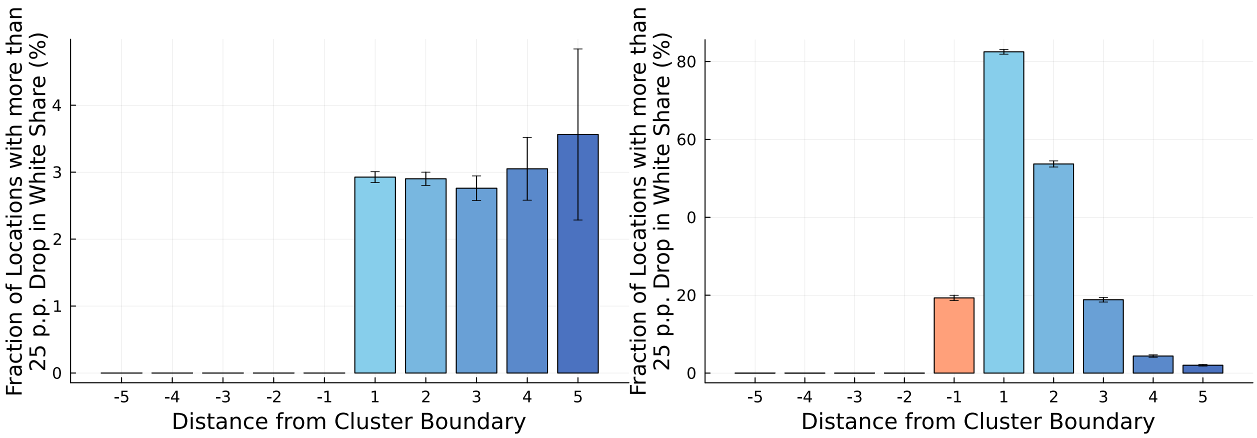
are inside of a Minority cluster and positive integers to locations inside a White cluster. For example, a White-mode tract bordering a Minority tract is assigned the location 1, those further inside the White cluster being assigned in turn $\{2, 3, \dots\}$. We then provide diagrams that show average or median characteristics of neighborhoods by distance from a cluster boundary.[18]

Figure 3 shows the median fraction Minority in this space for the simulated bounded neighborhood and spatial proximity models. Instead of displaying a single realization of the simulation as in Figure 2, the bar plot shows averages across 1,000 random initializations of the models and focus on tracts in proximity to a cluster boundary. As there are no racial preference spillovers present in the bounded neighborhood model, Minority shares are predicted to drop precipitously when moving across the boundary of a cluster (Panel a). By contrast, Minority shares are changing more smoothly when crossing a cluster boundary in the spatial proximity model (Panel b) reflecting White preferences for market access to other White households. Similar precipitous (bounded neighborhood) or smooth (spatial proximity) changes are predicted for neighborhood prices, where in both models households with strong homophily preferences pay a price for self-segregation.[19]

A critical question in the segregation literature is how neighborhoods evolve inside the city

[18] In Figure A2, we illustrate, using Census data for tracts from the South Side of Chicago, how to move from tract populations to racial clusters, how to index the locations within clusters, and then how to form histograms to represent this information.

[19] We show predicted price patterns in appendix Figure A1.



(a) Bounded Neighborhood Model **(b)** Spatial Proximity Model

Figure 4: Locus of Racial Change from an Increase in the Minority Share from 20 to 25%

in response to a shock to the aggregate city Minority share. Much of this is motivated by the shocks of the two great migrations of Blacks to northern cities. Since our model features multiple equilibria, one needs to start with an initial equilibrium and then consider what happens relative to this baseline as we progressively raise the Minority share. We initialize the city with the original equilibrium Minority shares and then increase the citywide Minority share from 20% to 25% while simultaneously reducing the White share from 80% to 75%.[20] Figure 4 displays the resulting probability for experiencing drastic Minority share changes of 25 percentage points or more by distance from the Minority cluster boundary. In our bounded neighborhood simulations, the locus of such drastic changes is independent of the distance to any existing racial cluster. In our spatial proximity model, by contrast, the increasing Minority share is reflected in large changes in the locations proximate to the existing Minority cluster.

3 Evidence from a Panel of Cities

Our theory and simulations highlight four key contrasts between the bounded neighborhood and spatial proximity models. The first concerns the salience of racial clusters. The bounded neighborhood model has no intrinsic link across tracts and so no intrinsic mechanism to generate clusters. The spatial proximity model provides strong reasons to expect racial clustering to be important, as the same forces that lead to segregation within tracts also lead to clustering of same-group tracts.

[20]These changes are roughly in line with the average change in the Minority share observed in US cities between 1970 and 1980. See Section 3 for details.

A second key contrast concerns the locus of racial change in the face of shocks to aggregate levels of the groups. Just as the bounded neighborhood model has no mechanism to generate racial clusters, it likewise has no mechanism to explain how aggregate shocks translate to the *locus* for entry of new tracts by mode. The spatial proximity model, by contrast, says that change will be such as to preserve the clustering that exists, hence change happens at the boundaries of clusters.

A third key contrast concerns the Minority share at the boundary of clusters. The bounded neighborhood model has a bang-bang prediction in which the Minority share is unaffected by whether we are near or far from the boundary of clusters. By contrast, in the spatial proximity model, boundary and interior tracts are quite different due to the spillovers. As we demonstrated, this leads to a strong but not drastic gradient in the Minority share at the boundary of clusters.

Our fourth key contrast applies related logic to consider housing prices interior to and at the boundary of clusters. One additional dimension in this setting is the assumption of an asymmetry in the strength of racial homophily, which we assumed to be stronger for Whites than for Minorities. As with Minority shares, the bounded neighborhood model provides only a bang-bang prediction about price differences between Minority and White mode locations. There is no role for the location of the tract relative to the boundary of clusters. By contrast, the spatial proximity model has two key predictions. The first is that within the Minority cluster, there should be little variation according to distance to the boundary, consistent with our assumption of zero Minority homophily preferences – they will not pay a premium to be remote from White mode tracts. Second, as we move from the Minority mode into White mode tracts, there should be a potentially strong, but non-drastic gradient as we move further in.

A review of these contrasts highlights that the bounded neighborhood model makes quite sharp predictions. Clustering and racial neighborhood change arise in space only randomly. Changes in Minority share and housing prices are precipitous at the boundary of clusters. One can reasonably ask why one may want to examine such sharp hypotheses with data. We believe there are two good reasons. The first is that the bounded neighborhood model, explicitly or implicitly, is the foundation for nearly all formal empirical work on segregation in economics. The second reason is that we would like to establish magnitudes for the features that separate the models. Our hope is that highlighting the strong contrasts between the models and documenting their empirical importance will stimulate future work to assess how important the spillovers at the heart of the model are in specific experimental and policy contexts.

3.1 The Data

We examine these contrasts using U.S. Census data from 1970 to 2000. For these four censuses we have detailed information on the racial composition of census tracts as well as a rich set of covariates. Our panel data of cities derives from the replication data of Card et al. (2008a). We do not go beyond the year 2000 as we want to compare the results that we will show to their prominent investigation of tipping points. All data is harmonized to 2000 census tract geometries and, similarly to Card et al. (2008a), we focus on tracts that are located within 1999 MSA definitions.[21] We also supplement the racial composition data with tract-level housing price data from the Longitudinal Tract Database (LTDB). As in the preceding theory section, we focus on a dichotomous classification of race comparing non-Hispanic White households and Minority households, understood to be the complement. For simplicity and following the literature, we refer to the two groups as White and Minority households respectively.[22]

3.2 Schelling Racial Clusters in the Data

Casual inspection of maps that illustrate the distribution of population groups for particular cities are suggestive that racial clustering of tracts is quite important. We would like to go beyond this by providing a quantitative measure of the importance of this clustering and thereby distinguish predictions from our two models.

As detailed in the previous theory section, we achieve this by classifying census tracts according to their racial mode. We then define racial clusters as a set of contiguous tracts within an MSA with the same modal race that surpasses a threshold tract count. One can vary the choice of the minimum number of contiguous tracts that will constitute a cluster.[23]

We can then investigate the fraction of our total MSA population that lives in racial clusters. We do this for varying thresholds in Table 1. Keeping in mind that a typical-sized tract will have roughly 4,000 residents, a cluster of 5 tracts requires roughly 20,000 people living in

[21] We also follow the sample selection methods put forward in Card et al. (2008a) and exclude all tracts in which (1) the decadal population growth rate exceeds the MSA mean by more than five standard deviations, (2) the ten-year growth in the White population exceeds 500% of the base-year total population, (3) the MSA contains fewer than 100 tracts (after applying the previous criteria).

[22] During the time period considered, non-Hispanic White households constituted the majority of the population in our sample. We do robustness checks that split the sample by Black versus non-Black, with broadly similar results.

[23] The classification procedure is illustrated in Panels (a) and (b) of appendix Figure A2 for selected census tracts in Chicago's South Side.

Table 1: Percentage Population Living in Own-Race Clusters by Minimum Cluster Size

		5 Tracts			10 Tracts			20 Tracts		
Year	Minority Share	**All**	W	M	**All**	W	M	**All**	W	M
1970	18	**89**	96	54	**88**	96	49	**86**	96	42
1980	24	**86**	95	58	**85**	95	55	**84**	95	49
1990	29	**83**	94	58	**83**	93	56	**81**	93	52
2000	36	**80**	90	62	**79**	90	60	**78**	89	57

Notes: "Minority Share" is the share of the overall population which is not White Non-Hispanic. "W" refers to White and "M" refers to Minority. All numbers in percent.
Data Sources: U.S. Census

contiguous same mode tracts. At this cutoff, and in all years we observe, between 80% and 89% of all Americans live in own-race racial clusters. Even if we raise the threshold to 20 tracts to constitute a cluster, this number changes little.

There is variation across groups. And it is important to be clear on what the aggregate and by-group numbers reflect. If a traditional dissimilarity index equaled zero, so both groups have identical distributions across locations, then by virtue of its majority status, Whites would have 100% of its population living in own-race clusters and Minorities would have 0% of their population in own-race clusters. Defining a cluster as 5 or more contiguous tracts, in the data the share of Whites living in own-race clusters ranges across the decades between 90-96%. So Whites consistently have close to their theoretical maximum and raising the minimum cluster size hardly affects this. Under the 5-tract threshold for a cluster, a majority of the Minority population lives in own-race clusters throughout our periods. This falls somewhat for larger minimum clusters, but reaches 62% at a threshold of 5 tracts in 2000. In summary, Schelling racial clusters are very prominent features of the data in all decades, even by the more stringent measure focused on Minorities.[24]

3.3 The Locus of Racial Change in All MSAs

An aggregate shock that increases the Minority share of a city will also change the allocation of space between neighborhoods for each distinct group. The bounded neighborhood model, by the very nature of being *bounded*, provides no prediction about *where* the new Minority neighborhoods will arise. It suggests that the likelihood of change solely is a function of the initial Minority share of a tract. By contrast, a central prediction of the spatial proximity

[24] The contrast in shares for Whites and Minorities is an illustration of the maxim by Anderson (2015) that many Minorities as a condition of their existence must live in White space.

model is that change is concentrated at the boundaries of racial clusters.

We can look at this with histograms pooling all MSAs in our sample for 1970-1980 in Figure 5a. Focusing on the middle panel, more than 50% of the tracts with a drastic change of 25 pp or more decline in the White population are in the boundary tracts at locations $\{-1, 1\}$.[25]

This actually understates the extent to which change happens at the boundary of clusters. Many tracts experiencing drastic change lie outside this range in tracts along an unbroken path of such change to the cluster boundary. In Figure 5b, we aggregate into location 1 the tracts contiguous to this that also experience such a drastic change. In this case, the amended locations $\{-1, 1\}$ account for roughly 80 percent of these drastic changes.

We can also examine in Figures 5a and 5b how this changes if we vary the cutoffs that define drastic racial change from 10 pp to 25 pp or 50 pp. We see that in each case change is centered on the tracts at the boundary of the Minority cluster and that the more drastic the change contemplated, the greater the concentration near the boundary of clusters. Appendix Figures A5 and A6 further confirm that this pattern also holds true for changes in the 1980s and 1990s.

For the pooled MSAs, all thresholds for drastic change, and all periods, a simple message emerges: drastic racial change is powerfully concentrated at the boundary of racial clusters.[26]

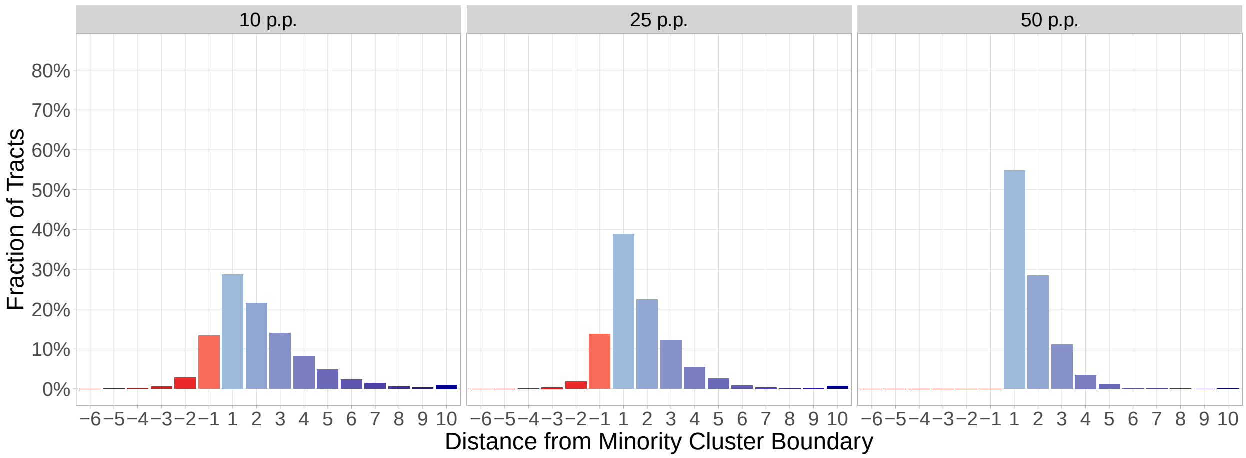
3.4 Clusters, Location, and Patterns of Segregation in the Data

Our models have distinct predictions about how the Minority share will vary at the boundary of clusters. Again, the very nature that the bounded neighborhood model is *bounded* means that the boundary between clusters has no special character. There should be a discrete jump of the Minority share when moving across tracts between a Minority versus White cluster. By contrast, our variant of the spatial proximity model predicts that the Minority share may vary strongly as we move across the boundary of clusters, but that the gradient will not be precipitous.

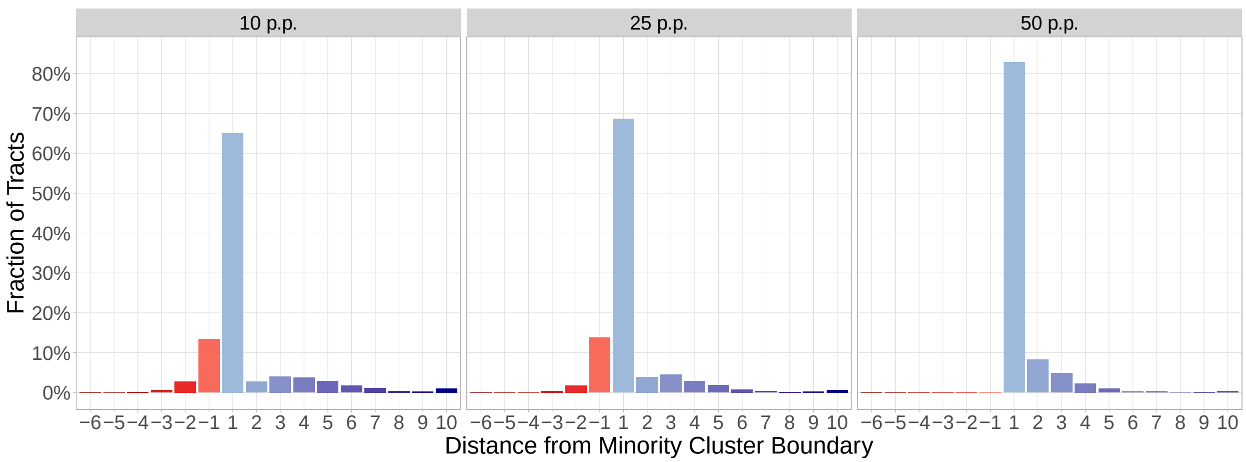
To investigate this empirically we slice through the census data in the same manner that

[25] A possible concern when investigating the location of all tracts experiencing drastic change is that differences in the number of tracts at each distance bin could drive results. As a robustness check appendix Figure A6 shows the fraction of tracts at each distance bin experiencing drastic racial change. The dominant pattern of racial change at the boundaries of clusters is equally salient in this figure.

[26] See also the ECDFs for percentage point White change for a tripartite spatial split in appendix Figure A8.



(a) By Location



(b) Contiguous Tracts to Boundary

Figure 5: Change in White Share of X p.p. or more, All MSAs 1970-1980

Notes: Out of 35,725 tracts in the 1970-1980 sample, 9,132, 3,845, and 825 tracts experience more than a 10, 25, and 50 p.p. change in their White share, respectively. Probabilities in each pane sum to 100%. Panel (b) aggregates to location 1 all tracts with a greater than 25 pp decline in the White share that are connected to the cluster boundary through a continuous path of such tracts.

we used to display our simulation results. We identify cluster boundaries in each MSA and then classify tracts according to their distance from the boundary.[27]

Evidence from all MSAs appears in Figure 6. An examination of the gradient at the boundary for all decades reveals that it is steep, but non-precipitous. This favors the spatial proximity approach. Within this approach, the mixed neighborhoods at the boundary reflect the will-

[27] This is illustrated in panel (c) of appendix Figure A2. The boundary is treated as the origin with distances $\{1, 2, \ldots\}$ assigned to White mode tracts and distances $\{-1, -2, \ldots\}$ for the respective Minority tracts. Tracts further to the interior of Schelling racial clusters have darker shades. Panel (d) projects these locations onto a simpler space displaying distance to the boundary of racial clusters on the X axis and median Minority shares on the Y axis.

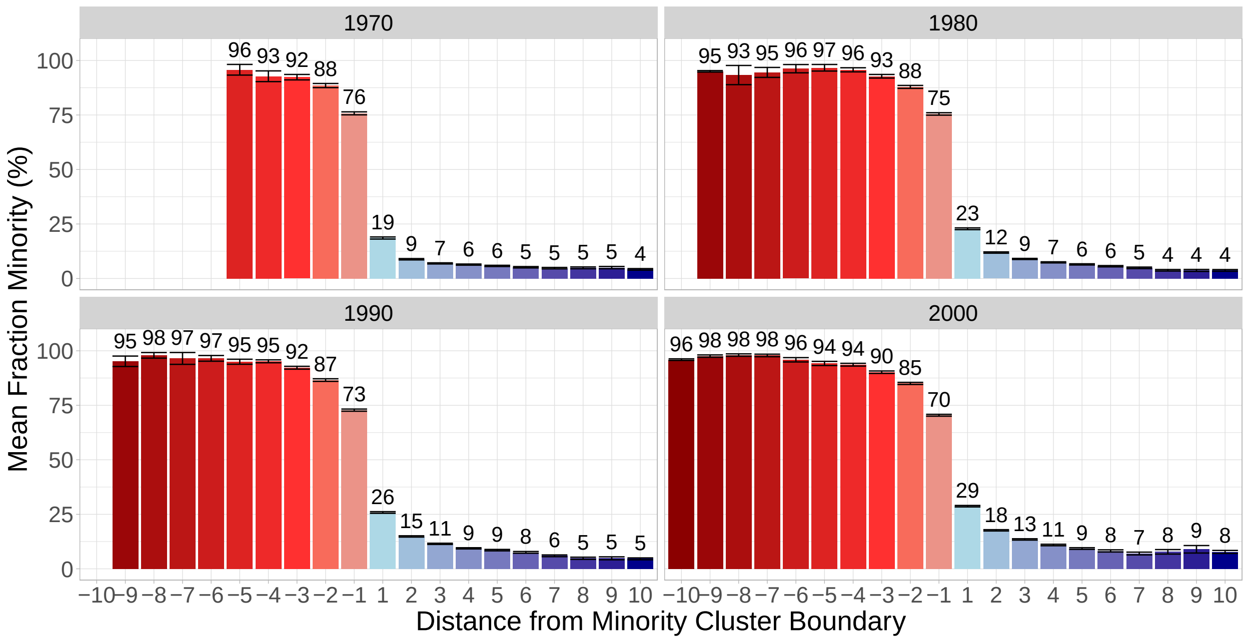


Figure 6: Mean Minority Share by Location, All MSAs, 1970-2000

Notes: 95% confidence bands are provided for each mean. The numbers at the top of each bar are the point estimates.

ingness of Whites with particularly strong Gumbel draws for those boundary neighborhoods to live in racially mixed neighborhoods that also feature lower prices.[28]

A natural concern is whether some of this non-precipitous gradient arises due to the boundaries of census tracts not coinciding exactly with the actual racial boundaries of the neighborhood. One cannot entirely dismiss this concern. But the fact that the gradient becomes notably less steep in later decades, when racial attitudes of Whites became more tolerant, suggests that this is not the only force at work, and so again is evidence favoring the spatial proximity model.[29]

[28]The results are broadly similar if we instead divide the groups into Black and non-Black. We see this for Chicago in Figure A3 and all MSAs in Figure A4.

[29]As Glaeser and Vigdor (2012) document, 1970 represents a peak period of segregation in U.S. MSAs as measured by the dissimilarity index, and they argue that the evolution represents the "end of the segregated century." By the scalar dissimilarity index, this is absolutely correct. But Figure 6 underscores that the advances are uneven. The Minority share in Minority mode clusters remains virtually unchanged as we move further to the interior, and indeed expand in size from 5 layers to 6. Most of the change in the dissimilarity index would appear to be a softening of the border gradient and a rise in the Minority share in White mode clusters. When we examine instead Black-Non-Black, there is change, but it is more limited (see Figures A3 and A4). This is progress, but only partial.

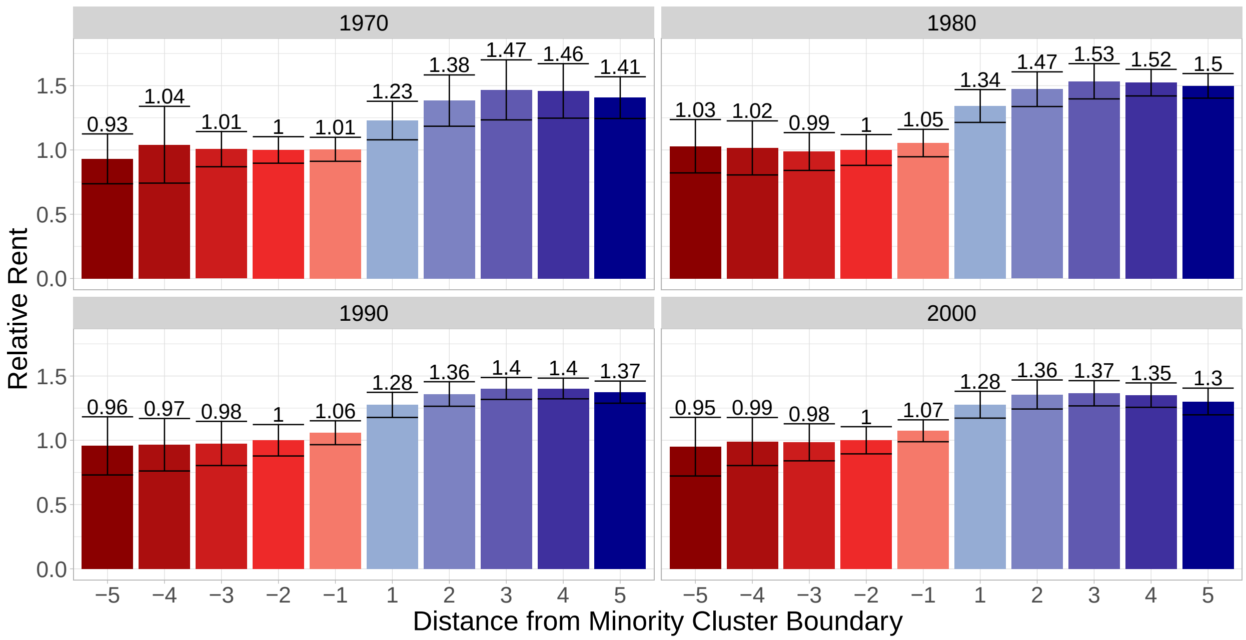


Figure 7: Relative Rental Prices, All MSAs 1970-2000

Notes: 95% confidence bands are provided for each mean. The numbers at the top of each bar are the point estimates.

3.5 Price Gradients by Distance from Cluster Boundaries

Our two models provide distinct predictions about how housing prices should behave inside and at the boundary of the respective clusters. Both models predict that since Whites have higher homophily preferences, they will pay a premium to occupy locations with a high White share.[30] For the bounded neighborhood model, this will be bang-bang, so that there will be a discrete jump at the boundary of racial clusters. Our version of the spatial proximity model, by contrast, has two predictions. The absence of homophily preferences by Minorities implies that housing prices in the Minority clusters should not vary by distance to the boundary. But Whites should pay a premium that is rising from the border of the boundary. As suggested through our simulation, this pattern should arise even in the absence of other neighborhood fundamentals that vary across space.

Empirically, we can investigate this using tabulated rental price data from the Census. To make prices easily comparable across cities, locations, and decades, they are first normalized by the city-specific median rent and then expressed relative to the rent paid in Minority-mode tracts that are 2 tracts away from the racial cluster boundary.

[30] This is consistent with the evidence from Cutler et al. (1999) that by 1970 "decentralized racism" leads Whites to pay more for equivalent housing. Here we explore the spatial patterns of these differences as we move from the boundary into the respective racial clusters.

The results can be examined in Figure 7. Within the Minority cluster, the relative homogeneity of prices is particularly striking in 1970 and 1980. Under this interpretation, the fact that in the later decades prices rise somewhat within the Minority cluster as we approach the boundary would indicate for Minorities a positive valuation for living in these more mixed race tracts within which they are still the mode and for Whites there a smaller discount required to live in these neighborhoods. In all decades, there is a rising price gradient as we move within the White cluster away from the boundary with the Minority cluster. Very similar patterns can be observed for relative home values displayed in appendix Figure A7.

3.6 Summary of Empirical Evidence

Overall we interpret this empirical evidence as being strongly in line with the predictions of our simulated spatial proximity model. Racial clusters are a ubiquitous feature of US cities across all time periods of our investigation. Racial change is highly concentrated at the boundary of clusters and the more drastic the change contemplated, the more it is concentrated at this boundary. Minority shares change steeply but non-precipitously at cluster boundaries. Rental prices show little variation internal to Minority clusters, but rise strongly as we move from the boundary to the interior of White clusters.

We would like to emphasize that while the evidence we provide for the relevance of spatial spillovers is not causal, it remains highly suggestive. For example, one might be concerned that sorting by income, in combination with spatially correlated residential amenities exogenous to racial sorting, could explain part of the observed clustering in the cross-section. We are not over-concerned about this case. There are significant differences in mean income between Whites and Minorities, but there is still substantial overlap in these distributions during the time periods we consider. If racial clustering was truly due to income sorting, then we would expect to observe substantially more spatial integration of households with similar income but different race than we see empirically.

When considering alternative explanations, such as income sorting, spatially correlated labor market access, or discrimination in the housing market, it is important to keep in mind that, in principle and ex-post, the bounded neighborhood model can rationalize any spatial distribution of Whites and Minorities simply through the adjustment of the race-specific exogenous fundamentals η_{rj}. It can also match any dynamics through respective changes to those exogenous shocks across periods. However, it does not provide an endogenous explanation for why these shocks should evolve precisely in the way necessary to generate the data. By contrast, and as we show here, the spatial proximity model can endogenously generate patterns that both match the cross-section as well as the dynamics of racial residential segregation remarkably well. We therefore believe that spatial spillovers in racial preferences provide a parsimonious explanation for what we observe and so are key in rationalizing the cross-section and dynamics of neighborhood racial change.

4 Evidence on Location and Tipping for All MSAs

One of the main predictions of the spatial proximity model is that drastic racial change is concentrated at the boundaries of racial clusters. In our empirical investigation focusing on decadal changes in census tracts' racial composition we found strong supportive evidence for this pattern. This result stands in strong contrast with the evidence presented by Card et al. (2008a). The authors develop a reduced form approach to identify tipping points at the MSA-level using the same census data. They find significant tipping points for many cities, compare the location of tipping points across cities, and track their development over the decades from 1970 until 2000. In their section investigating the geography of tipping, Card et al. write that "*Taken together, these results are not consistent with the predictions of the expanding ghetto model. Tipping effects are, if anything, strongest far from the existing ghetto. We conclude that this model cannot account for the nonlinear dynamics we see [. . .]*" (Card et al., 2008a, p. 205).[31]

How did Card et al. (2008a) end up with a conclusion regarding the locus of racial neighborhood change that is so fundamentally different from ours? To understand their results better, we revisit their findings. This comes in two parts. The first will examine in detail a case study for Chicago in the period 1970-1980. We will then use insights from this case study to re-examine all MSAs in the three decades 1970-2000 of our study. We will see that we arrive at different results due to a theoretically-motivated spatial stratification that emphasizes distinct social processes in different regions of the MSAs.

4.1 A Re-examination of Chicago, 1970-1980

The most striking visual evidence supporting the tipping hypothesis appears in Card et al. (2008a) as their Figure 1. Examining Chicago in the period 1970-1980, they find that when the initial Minority share of a census tract passes a tipping point of 5.7%, there is a discontinuous drop in the decadal growth of the White population in excess of 30 percentage points. Exactly because this appears to provide powerful evidence in favor of the tipping

[31] Card et al. (2008a) cite Möbius and Rosenblat (2001) as representative of the "expanding ghetto model." However, the latter's approach is built on Schelling's bounded neighborhood model, which we take as the key underlying theoretical foundation.

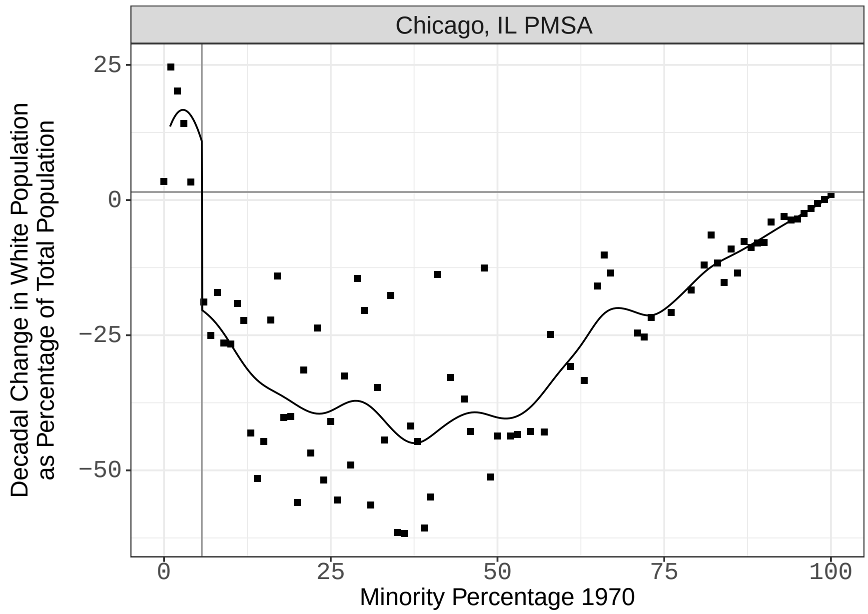
hypothesis, we find it a propitious setting to explore the varied forces at work. Because our theory emphasizes spatial aspects of the evolution of racial neighborhood change, it is a big advantage as well to investigate a specific city where maps can shed light on these forces. Of course, our case study of Chicago in the period 1970-1980 is just a single example. Hence in Section 4.2 we will explore whether the insights we gain from this example are present when we look at the data for all MSAs taken together over the entire period 1970-2000 of our study.

We begin, then, by reproducing the Card et al. (2008a) Figure 1 as the top panel of our Figure 8. This plots the binned change in the White population 1970-1980 as a share of the tract's 1970 total population on the vertical axis against a tract's initial Minority share in 1970 on the horizontal axis.[32] The vertical line in Figure 8 is the posited tipping point of 5.7% in 1970 for Chicago using Card et al.'s preferred fixed point method. The horizontal line is the unconditional mean for the change in White population. We can take these vertical and horizontal lines as defining quadrants that will be helpful in our discussion of the evidence for tipping.

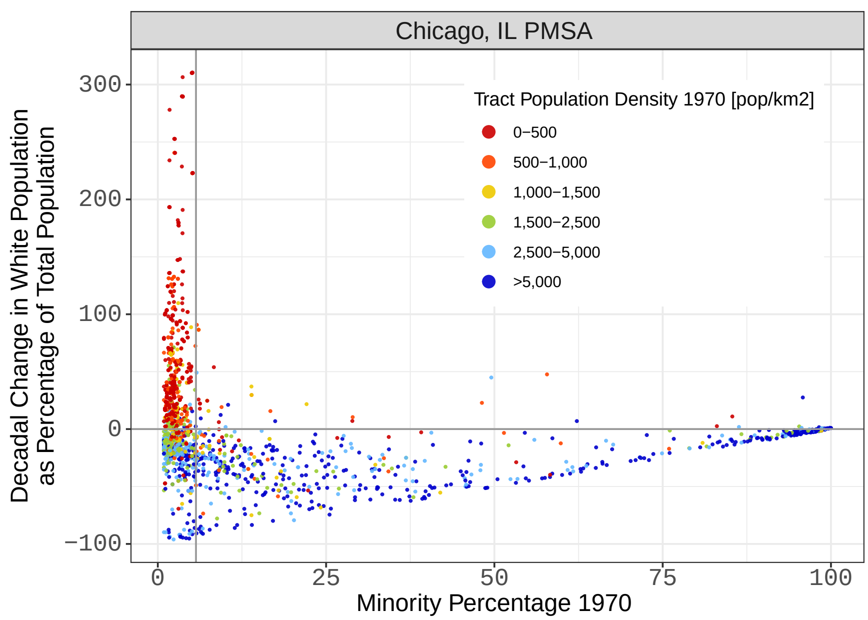
The partial equilibrium bounded neighborhood model that Card et al. (2008a) rely on closely resembles the bid-rent functions we presented in the theory section and it has clear predictions about how locations should evolve above and below the tipping point. Tracts above the tipping point in the initial period should see a loss of White population in the subsequent period. This is powerfully supported in the binned data, as the first quadrant is entirely empty, hence all of the binned observations are in the fourth quadrant, showing a decline in the White population.

Below the tipping point, the theory holds that the locations should be racially stable, hence we would hope to see the data clustered around zero White population growth. The binned data below the tipping point is not perfect in this respect. Two of these bins are close to zero White population growth, while others show growth of 13% to 25%. The third quadrant (declines in White population and below the tipping point) is entirely empty in the binned data. In short, while less than perfect, the contrast between the change in the White population growth just below and just above the tipping point in the binned data appears to provide powerful evidence in favor of the tipping hypothesis.

[32] To be precise, the y-variable is defined as "(tract-level White population in 1980 minus tract-level White population in 1970) divided by tract-level total population in 1970." Tract geographies are standardized at 2000 Census geographies to allow for cross-decadal comparisons. This y-variable is the same as used in Card et al. (2008a); we maintain their restrictions to the set of tracts in the estimation sample, which are explained in-depth in their paper.



(a) Binned Data for Chicago



(b) Unbinned Data for Chicago, with Density

Figure 8: Binned and Unbinned Neighborhood Change, Chicago 1970-1980

Notes: Panel (a) contains 100 scattered points of width 1 percent (in terms of Minority percentage) which represent the average change in White population for all tracts in that Minority percentage band. A kernel mean smoother is overlaid. Panel (b) illustrates the unbinned, raw data. The vertical line represents the fixed-point estimated tipping point for Chicago in 1970 (5.7%). Colors in Panel (b) indicate tract population density.

Naturally, binning shrouds heterogeneity. But the heterogeneity may provide insight to the forces contributing to the discontinuity at the tipping point. So we next turn to the unbinned data for Chicago, which we show in the bottom panel of Figure 8. While unbinning the data will yield more heterogeneity, we would like it not to fundamentally change the conclusions we drew from the binned data.

Consider first the unbinned data above the tipping point. Theory predicts that these tracts will show a loss in White population. And this is overwhelmingly what we see in the unbinned data. There are a modest number of tracts in quadrant 1, reflecting a rise in the White population, but the vast majority of observations are in quadrant 4, reflecting a loss of White population. The unbinned data strongly endorses the conclusions from the binned data about evolution past the tipping point.

Now consider the unbinned data below the tipping point. Again, the partial equilibrium bounded neighborhood theory tells us these tracts should have a stable White population. The binned data exhibited this stability, if imperfectly. When we unbin the data for the tracts below the tipping point, though, what we see is a veritable explosion of heterogeneity. Instead of seeing the data clustered around zero White change, we see tracts with a change of White population ranging from close to -100% to above 300%. This explosion of heterogeneity below the tipping point is not something the bounded neighborhood theory predicted, so we would like to explore it further.

A first step in this exploration takes advantage of another feature of the unbinned data presented in the lower panel of Figure 8. Specifically, we have used colors to distinguish population densities of the tracts. At one end, dark blue indicates a population density of $5,000$ or more per square kilometer, while at the other end, dark brown indicates a population density below 500 per square kilometer. Above the tipping point, the observations are overwhelmingly high density and concentrated in the third quadrant. Below the tipping point, there is a sharp contrast. Those in the second quadrant, hence with strong White population growth, are overwhelmingly low density. Those in the third quadrant, with strong declines in White population, tend to be high density. This is a dimension of the data not properly situated in the theory.

Since we are looking at Chicago just in the period of 1970-1980, we can explore more directly the spatial patterns suggested by this variation in density. We implement this in Figure 9. There we simply plot on a map of the Chicago MSA the data colored according to the quadrant in which it appears in the unbinned data. The tracts above the tipping point that lose White population, hence the dark red-colored tracts in the fourth quadrant, are heavily

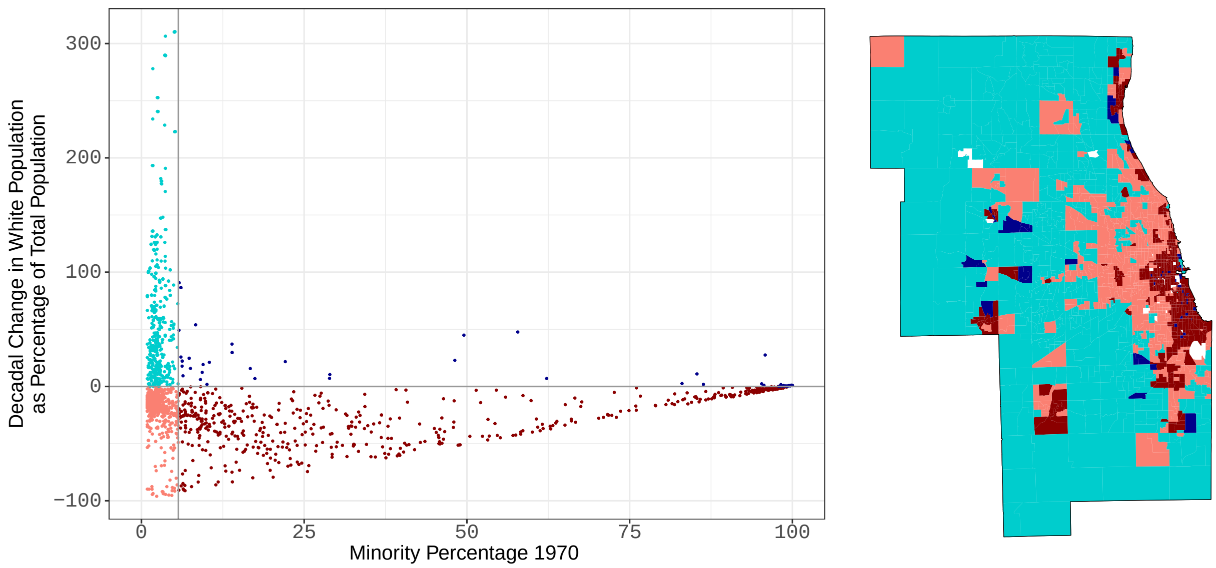
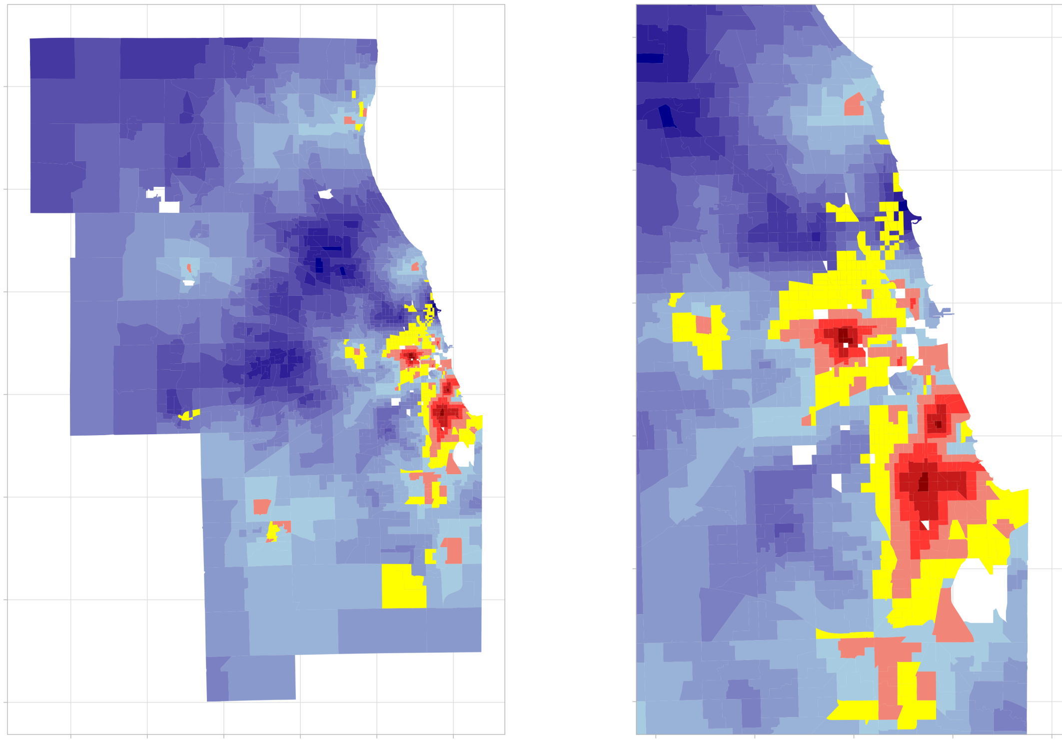


Figure 9: White Population Change by Quadrant, Chicago 1970-1980

concentrated in central Chicago and its South Side. The modest number of dark blue-colored tracts above the tipping point that gain White population in quadrant 1 appear to have a higher tendency to be more remote from the center of Chicago. Below the tipping point, the salmon-colored tracts in the third quadrant that lose White population are for the most part at the outer boundary of the dark-red tracts that dominate above the tipping point. Finally the light blue tracts of the second quadrant that are below the tipping point but have powerful growth of the White population are primarily remote from the central city, i.e. suburban.

One of the central conclusions from our examination above of the dynamics of segregation in Section 3 is that change happens at the boundary of clusters. We can revisit this for our case of Chicago 1970-1980. In Figure 10, we color as yellow all tracts that had a decline of 25 pp or more in the White population. We can see that these are overwhelmingly concentrated at the boundary of the White and Minority clusters.

We can examine this drastic change with more granularity in Figure 11 by plotting a dot map of changes in population by group at the census tract level. The dot map shows the net entry and exit of Whites and Minorities by census tract, with each dot being either a star, representing a net entry of 75 people, or an open circle, representing a net exit of 75 people. Summing dots per census tract gives the total change by group for that tract. Zooming into this dot map for the South Side of Chicago around the University of Chicago, we observe intense churning right at the boundary of the racial clusters, with the entrance into White-mode boundary tracts by Minorities (represented by red stars) coupled with White exit from



(a) Entire MSA　　　　**(b)** Central City

Figure 10: Drastic Loss of White population, Chicago 1970-1980

Notes: Tracts colored yellow lost 25 pp or more of White population.

these tracts (represented by blue circles).

Even these very simple approaches to visualizing the data indicate that they contain powerful spatial patterns. This suggests, as well, that simply pooling all the observations to identify an MSA-specific tipping point risks conflating very different social processes in the different locations. The next section seeks to understand these spatial elements in more depth.

4.2 A Spatial Stratification for all MSAs

We now turn to examine the data for all MSAs in our sample from 1970-2000. We want to do so in light of what we learn from the detailed case of Chicago 1970-1980. This examination will build on the approach of Card et al. (2008a), but looking through a different spatial prism and tying what we do more closely to the underlying theory.

One lesson comes through powerfully from our case study of Chicago: Location matters. Central urban areas, close to existing Minority clusters, evolve differently than more remote urban areas. And urban and suburban areas evolve differently.

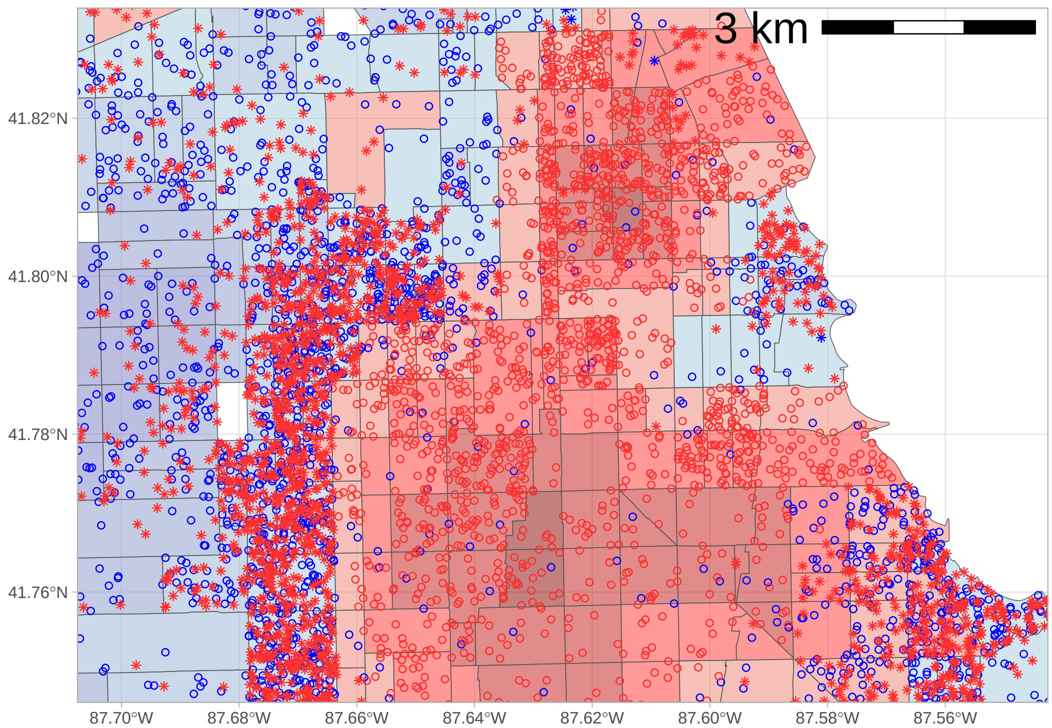


Figure 11: Entry and Exit by Race, South Side of Chicago, 1970-1980

Notes: Dots on the map represent bins of people, colored blue for Whites and red for Minorities. An open circle represent a loss of 75 people of a given type in that tract. A star represents a gain of 75 people of a given type in that tract. Sum of dots in each tract represent the total inflow or outflow of Whites and Minorities from the tract between 1970 and 1980. The base color of census tracts is the racial mode of that census tract in 1970, with lighter shades representing tracts closer to a boundary.

We can tie each of these locational characteristics to elements of our underlying theories. Restricting attention to urban areas, the spatial proximity model holds that drastic change should be most powerful in tracts close to the boundary of the existing Minority cluster. The bounded neighborhood model focuses only on the racial characteristics of the tracts themselves, so says proximity to the existing Minority cluster should not matter. Evolution in urban areas remote from the boundary of racial clusters thus provides an unconfounded test of pure tipping in the bounded neighborhood model. Suburban areas should be little affected by tipping, i.e. White exit in response to Minority entry. Instead, they should experience tremendous White entry (Boustan, 2010), with White avoidance of areas with higher levels of Minorities (Ellen, 2000). They should experience what we term *biased White suburbanization*.

We can operationalize these by first dividing urban from suburban tracts as those with an initial population density respectively above or below 1,000 per square kilometer.[33] We can further divide the urban tracts into those more- versus less-exposed to Minority clusters, at locations of $l \leq 2$ versus $l > 2$ relative to the boundary of the racial clusters.

We can have a first view of the appropriateness of this spatial partition by plotting the pooled all-MSA data for 1970-1980 in Figure 12. The X-axis shows the 1970 Minority share relative to the metro-specific tipping point. The Y-axis shows the change in the White population from 1970 to 1980 relative to the initial total tract population. The data is partitioned both according to location, i.e. urban more-exposed, urban less-exposed, and suburban, as well as according to whether the tract observed is above or below the metro-specific tipping point.

A first fact leaps out from Figure 12: The urban and suburban tracts demonstrate radically different experiences. The urban areas are dominated by White exit and the suburban areas by White entry. Even suburban tracts *above* metro-specific tipping points are largely dominated by White entry. The quite distinct social processes call into question the appropriateness of the headline results of Card et al. (2008a), which pool all of these results and call them tipping.

The differences between the two urban groups are more subtle. Both feature substantial White exit, even for tracts below the posited tipping point. This is more pronounced among the urban more-exposed tracts and will be examined more closely in the regression analysis below.

[33]We adopt the "urban" vs. "suburban" terminology for simplicity. More properly the latter should be thought of throughout the discussion of all-MSA data as an area with opportunities for suburban expansion.

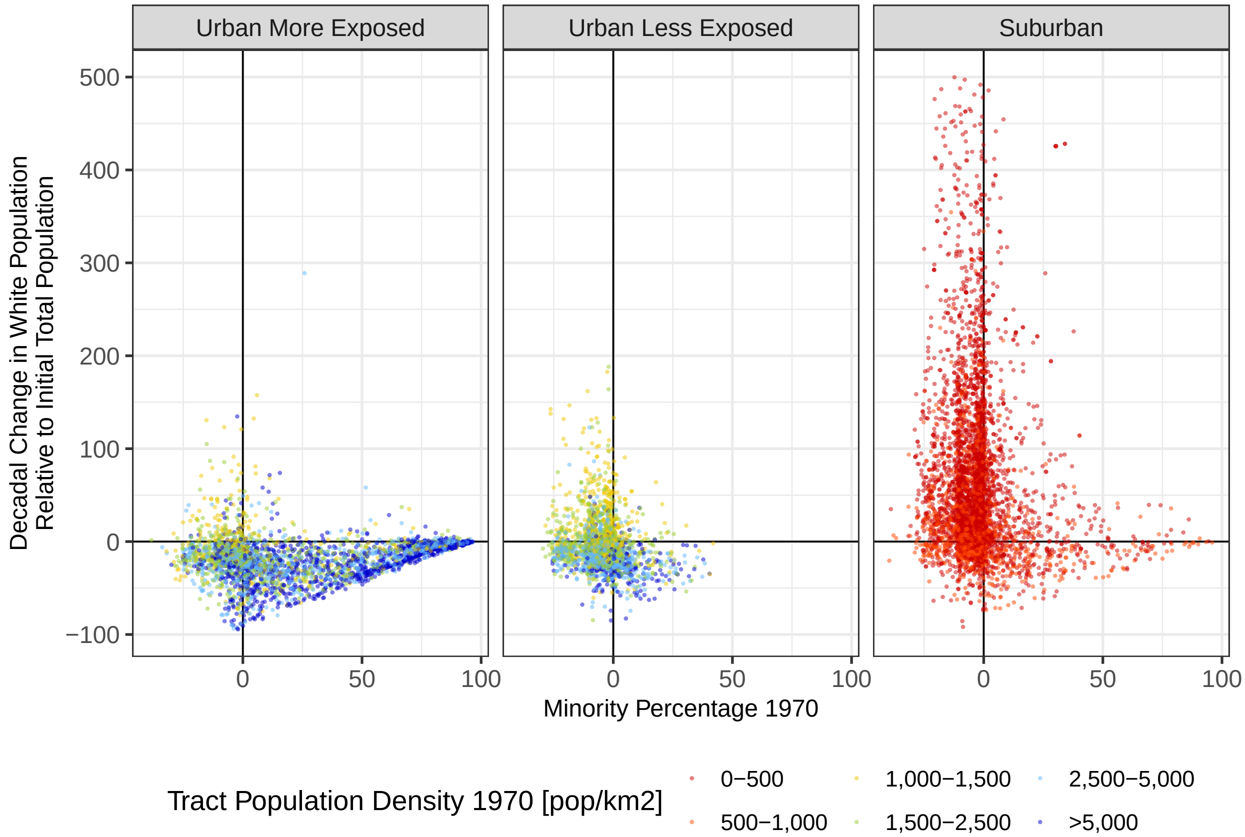


Figure 12: White Population Level Changes by Geographic Split, All MSAs 1970-1980

The bottom of Table 2 provides summary statistics on both overall and drastic racial change which confirms that our sample period 1970-2000 was one of strong racial evolution. The White share of our 100+ MSAs fell on average roughly 7 percent each decade. Yet there was substantial heterogeneity across locations within the MSAs. The White share in the urban more-exposed locations fell on average more than 11%, while this was only roughly 3% in suburban areas. The 1970s were the period of most dramatic change. In that decade, drastic change of a fall in the White share of 25 pp or more occurred in nearly 25% of tracts in the urban more-exposed areas but less than 4% of those in the suburban areas. The differences in this dimension remained substantial in all periods. The experience of the urban less-exposed areas in these measures always fall between the other two.

Our visualization and summary statistics for the all-MSA data confirm a fundamental fact: There are dramatic differences in the racial evolution of urban and suburban tracts, and more subtle differences even among urban tracts more- versus less-exposed to the boundary of racial clusters. In the section that follows, we will replicate the all-MSA regressions from Card et al. (2008a) that pool these locations. Because we view pooling as conflating quite distinct social processes, however, our emphasis will be on the spatially stratified regressions that follow, which also can be tied to elements of our theory.

4.2.1 Methods and pooled regressions

For purposes of comparability, we will stay methodologically close to the approach of Card et al. (2008a), yet distinct in the spatial stratification we develop and in the theory within which we interpret results. Their approach proceeds in two steps. In their preferred "fixed point" method, they first identify an MSA-specific tipping point as the Minority share at which the White population grows at the same rate as the MSA as a whole. Having used two-thirds of their data to identify candidate tipping points, the remainder of the data is then pooled across MSAs and used to estimate the magnitude of the jump at the discontinuity, relying on a regression discontinuity design using quartic polynomials, MSA fixed effects, and several tract-level controls.[34] For simplicity, we follow the same procedure. Importantly, however, we are going to test for the magnitude of tipping points separately across different strata of the pooled data by running our regressions separately on the three individual subsamples. The pooled discontinuity will not necessarily be an average of the three subsamples, because the estimated discontinuities are derived from separate polynomials fit for each subsample.

Table 2 shows our estimation results for tipping for all MSAs from 1970-2000 both in the pooled version that was the centerpiece of Card et al. (2008a) and in a spatially stratified version. We examine two types of dependent variables, which for concreteness we refer to as "levels" and "shares." The first (levels) is the change in the tract's by-group population divided by the total initial population. The range of feasible outcomes for the change in levels is $[-100\%, \infty)$. This allows comparability with the core results of Card et al. (2008a). It also focuses attention to changes in by-group population *levels*, so helps to sharply distinguish the social processes evolving in the urban versus suburban areas.

The second dependent variable we will consider (shares) is the change in the tract White share. The range of feasible outcomes in shares is symmetric $[-100\%, 100\%]$. One attraction

[34] We discussed in Section 2.2 why it might be difficult empirically to distinguish drastic racial change associated with elastic White responses to a Minority share shock from a true tipping bifurcation. Card et al. (2008a) sidestep this issue when they emphasize that there may instead be a steep downward sloping (but continuous) curve in the neighborhood of their "tipping" points rather than a true discontinuity. If one were to take the discontinuity seriously, the appropriate specification would use local linear regressions. We have implemented these with population weighting and find that the measured discontinuities are insignificantly different from zero. But this may be taking the strict discontinuity too seriously. For these reasons, and for comparability, we follow their approach. This should be kept in mind when we use the terms "tipping" and "discontinuity," where we adopt their usage in reference to results in the all-MSA regressions.

of this alternative is that the theoretical derivation in Card et al. (2008a) leads to a focus on the racial share, not the level.[35] And, of course, the main point of the tipping literature is to understand the change in racial composition. We will learn a great deal, though, by comparing levels and shares results.

For each decade between 1970 and 2000, Table 2 shows estimated tipping discontinuities for the Minority, White, and total population. We run our regressions separately on the three individual subsamples. In addition to the estimated tipping discontinuities, the table shows for each decade and each stratum the number of observations used for the regressions, the average change in the tract-level White share, as well as the fraction of tracts experiencing a drop in their White share of 25 percentage points or more (i.e. drastic racial change).

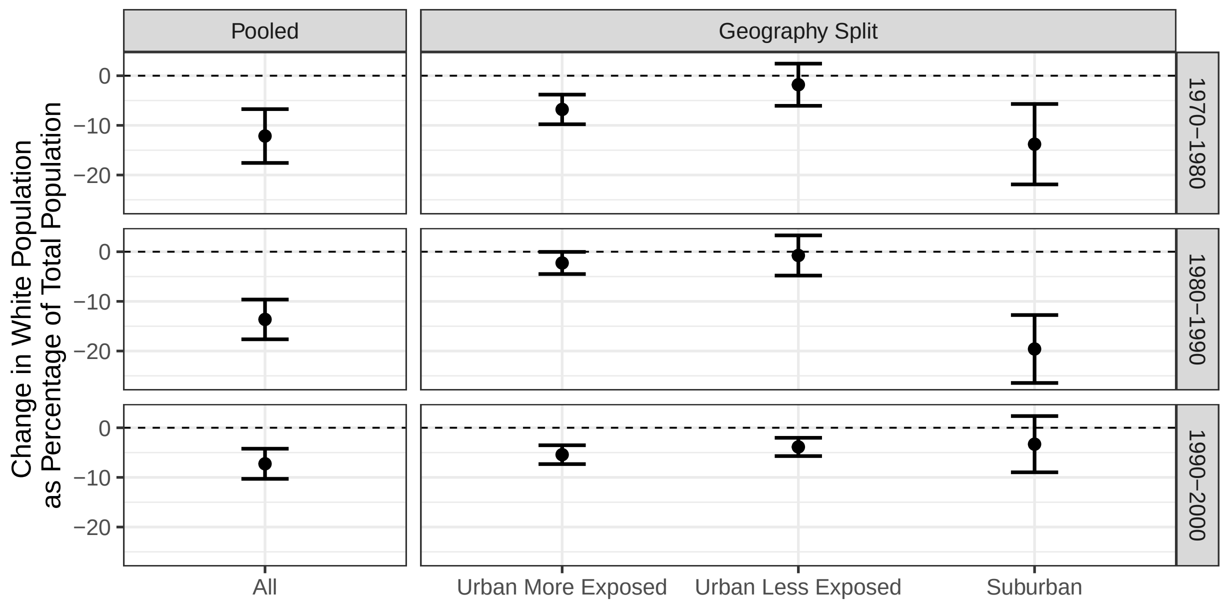
The first column of Table 2 replicates the pooled results from Card et al. (2008a). In each of the decades, when the initial Minority share crosses from just below to just above the posited tipping point, there are modest and sometimes insignificant changes in Minority population; sharp drops in the White population; and consequently equal magnitude drops in total population. Card et al. (2008a) interpret the discontinuity in the White population as tipping, where the tipping discontinuities are $(-12\%, -14\%, -7\%)$ for the 1970s, 1980s, and 1990s respectively. We display these estimates visually in the first column of Figure 13a.

[35] They acknowledge this, but explain the shift to levels based on the observation that their theory does not provide for the expansion of housing and population, phenomena present in their data. However they do not present any reason that these matter for their underlying theoretical predictions. Indeed, the theory that yields shares as the appropriate dependent variable is the entire basis for pooling observations at the MSA level, given that the cross section within an MSA itself has considerable variation in population, housing, and the opportunities for expansion of each. Examination of levels, as noted, introduces a fundamental asymmetry in the range of feasible outcomes that taken alone may cloud interpretation.

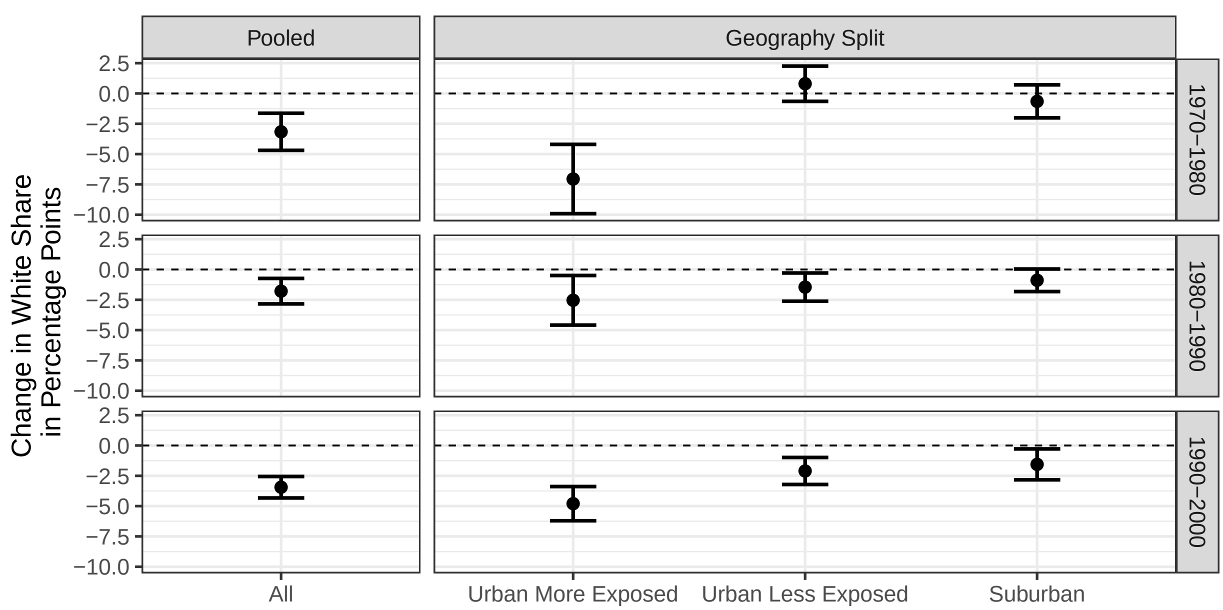
Table 2: Estimated Tipping Discontinuities, Pooled Sample and Three Groups by Geography

	Pooled	Triple Split		
		Urban More Exposed	Urban Less Exposed	Suburban
1970 - 1980				
Change in White population	-12.1	-6.8	-1.8	-13.8
	(2.7)	(1.5)	(2.1)	(4.1)
Change in Minority population	2.0	7.6	-1.5	-2.1
	(1.0)	(1.7)	(1.0)	(2.3)
Change in total population	-10.1	0.8	-3.3	-15.9
	(3.0)	(1.7)	(2.3)	(4.9)
Change in White share	-3.2	-7.1	0.8	-0.7
	(0.8)	(1.4)	(0.7)	(0.7)
Average Change in White share	-8.0	-15.5	-7.0	-3.8
Fraction Change in White share < -25 p.p.	10.8%	24.8%	7.2%	3.8%
Observations	11,611	3,346	3,162	5,103
1980 - 1990				
Change in White population	-13.6	-2.3	-0.8	-19.6
	(2.0)	(1.1)	(2.0)	(3.5)
Change in Minority population	-1.1	0.2	1.6	-2.6
	(1.1)	(1.5)	(0.9)	(1.5)
Change in total population	-14.7	-2.1	0.8	-22.2
	(2.6)	(1.4)	(2.2)	(4.3)
Change in White share	-1.8	-2.5	-1.5	-0.9
	(0.5)	(1.0)	(0.6)	(0.5)
Average Change in White share	-5.9	-8.9	-5.6	-3.6
Fraction Change in White share < -25 p.p.	4.5%	8.6%	2.6%	2.2%
Observations	12,151	3,976	2,643	5,532
1990 - 2000				
Change in White population	-7.3	-5.4	-3.9	-3.3
	(1.5)	(1.0)	(0.9)	(2.9)
Change in Minority population	2.9	4.0	1.6	2.7
	(1.1)	(0.9)	(0.8)	(2.0)
Change in total population	-4.3	-1.4	-2.3	-0.6
	(2.1)	(0.9)	(1.2)	(4.1)
Change in White share	-3.4	-4.8	-2.1	-1.6
	(0.4)	(0.7)	(0.6)	(0.6)
Average Change in White share	-7.8	-9.9	-8.0	-5.6
Fraction Change in White share < -25 p.p.	6.9%	10.7%	5.0%	3.8%
Observations	13,371	5,478	2,543	5,350

Notes: Regressions performed on pooled sample of all MSAs as well as tracts split by population density and proximity to White and Minority cluster boundaries. The *levels* regressions use the decadal change in by-group population divided by the total initial population as the dependent variable. The *shares* regressions use the percentage point change in the White tract share. For each sample and decade, the average percentage point change in the White share and the fraction of tracts which experienced a drastic drop in White share of 25 p.p. or more are provided.



(a) Change in Levels



(b) Change in Shares

Figure 13: Geographic Splits and Tipping Point Magnitudes, All MSAs 1970-2000

4.2.2 Urban Less-Exposed

Next we move to the spatially stratified analysis using our tripartite split.[36] Results from this investigation are displayed in columns 2-4 of Table 2, are visualized in columns 2-4 of

[36] In table VII of their paper, Card et al. (2008a) provide a set of robustness checks that may appear similar to our spatial stratification. There they investigate if tipping discontinuities are significant (1) by central

Figure 13a, and the raw data that feeds into the regressions is shown in Figure 12.[37] The results for the regressions in shares are shown in the fourth row of each decade-panel in Table 2. They are also visualized in Figure 13b.

We start by focusing on the estimated tipping discontinuities in the urban less-exposed tracts shown in column 3 of Table 2. This should be the clearest case for finding the kind of tipping predicted by the bounded neighborhood model, since here the results are less prone to being confounded by concerns of the role of spatial proximity to the existing minority cluster or alternatively suburban tracts possibly prone to discontinuous White entry.

The results are stark. Tipping discontinuities in the urban less-exposed tracts are small and insignificant in all decades for Minorities and total population, as well as for Whites in the 1970s and 1980s. The only significant discontinuity for the urban less-exposed tracts comes for Whites in the 1990s. The measured discontinuity even in that period is only -3.9%, so in a substantive sense pretty modest.

When we turn to the shares regressions in the urban less-exposed area, the results are broadly similar. Discontinuities for White shares are always small (2% or less) and sometimes insignificant.

In short, the purest test of the bounded neighborhood model, in the urban less-exposed areas, suggests that tipping, when it can be discerned at all, is of very modest importance.

4.2.3 Urban More-Exposed

We next turn to the urban more-exposed area results. The spatial proximity model suggests these tracts should be more prone to drastic change, so perhaps also to tipping, because this area includes locations proximate to the boundary between the racial clusters.

city vs. remainder of the MSA, (2) by distance to the nearest high-minority-share tract, and (3) by having a neighboring tract with a minority share above the tipping point or not. In these three robustness checks, Card et al. (2008a) find that tipping effects are usually smaller in the central city, and larger when moving further away from high-minority-share tracts and tracts that are beyond the tipping point. This leads them to conclude that the expanding ghetto (spatial proximity) model cannot explain the tipping dynamics they observe. In all of the splits, however, their findings are driven by suburbanization and discontinuous White entry into low density tracts. Split (1) is prone to confounding because Card et al. (2008a) use 2000 central city definitions and thus include tracts in the central city that were not urbanized in the early decades. Splits (2) and (3) are affected since tracts that are far from existing Minority tracts also are predominantly located outside of the city center and are thus suburban. Our spatial stratification avoids these issues, first, because we classify suburban tracts, which are prone to discontinuous White entry, based on their population density and not on the 2000 central city indicator. Second, we consider distance from a Minority cluster as well as urban or suburban status simultaneously in the same stratification.

[37] We also examine the raw data separately for Chicago 1970-1980, with similar conclusions, in appendix Figure A9.

Our results in the levels regressions are as follows. In all decades, there are only small and insignificant effects at the tipping point for total population. In all decades, there are negative and significant declines in the White population at the tipping point. In both the 1970s and 1990s, the change in the Minority population at the tipping point is of opposite sign and similar magnitude as the growth in the White population. The one exception is the 1980s, in which there is a small and insignificant effect on the Minority population. This presence of Minority entry and White exit is consistent with tipping.

It is notable, though, that even in the more-exposed urban areas the magnitudes are not large in the levels regressions. In the 1970s, 1980s, and 1990s the tipping discontinuities in the White population are respectively (-7%, -2%, -5%). These changes are statistically significant and economically meaningful.

We now examine the White shares regressions in the urban more-exposed tracts. These discontinuities in the change in White shares for the 1970s, 1980s, and 1990s respectively are (-7%, -3%, and -5%). From the White levels regressions, we know that these are associated with little measurable change in population and that we primarily see the simultaneous entry of Minorities and exit of Whites in roughly the same magnitudes.

We find in all decades that in the more- vs. less-exposed urban areas that the absolute decline in the White share is larger and the fraction of tracts experiencing drastic racial change of a 25 pp or more drop in the White share is much higher.

The spatial proximity model does imply that drastic racial change will happen at the boundary of clusters, so the presence of larger measured tipping in the urban more-exposed areas is certainly in the spirit of the model, even if it does not imply that this must take the form of tipping.

Overall, though, the magnitude of changes in the White share in a decade even in the urban more-exposed areas is pretty modest. At least over the horizon of a decade, this seems remote from the drastic change of racial tipping in common discussion.

4.2.4 Suburban

We now examine levels results for the suburban tracts. Of our stratified areas, these most strongly parallel the Card et al. (2008a) pooled results. That may not be too surprising, given that especially in the first two decades suburban tracts constitute a plurality of all tracts.

The change for Minorities at the MSA-specific tipping point is small and insignificant in all decades. The discontinuities for the White and total population are even larger than in the spatially pooled regressions in the 1970s and 1980s, but insignificant in the 1990s. The White tipping discontinuities in the 1970s and 1980s, accordingly, are -14% and -20%, with even larger population discontinuities.

Even with this strikingly large measured tipping in the 1970s and 1980s, drastic decline in the White share of 25 p.p. or more occurred in only 2% and 4% of all suburban tracts in those decades. That is, the levels approach is finding powerful tipping effects precisely in a region in which drastic White exit is rare. This is in line with what we saw when we plotted the raw data in Figure 12. The suburbs, both below and above the tipping point, are dominated by White entry.

We can examine this, as well, with the share regressions. In this case, the discontinuities among suburban tracts are (-1%, -1%, -2%), with only the last being significantly different from zero.

On its face, this might seem a contradiction. The levels regressions are telling us suburban tracts experience dramatically different White growth in the first two decades on different sides of the tipping point. The shares regressions tell us that crossing the tipping point has tiny or precisely measured zero effects on the change in the White share of these tracts.

The reconciliation in these two perspectives comes from returning to basics. There is a racial story here, but it is not tipping. Tipping means something specific – Minority entry that induces White exit. But Minority entry to the suburbs in this period is minimal and White exit rare. Instead what we see is the kind of avoidance of Minority areas that supports "biased White suburbanization." Even spectacular White entry to these already low Minority share tracts hardly changes the racial composition.

5 Conclusion

This paper investigates the determinants of the cross section and dynamics of neighborhood racial segregation. A recent literature has demonstrated the importance of neighborhoods in shaping life opportunities. Our work is thus a step toward understanding whether interventions at scale that affect neighborhood racial composition may thereby change or even undo the intended benefits.

We nest Schelling's spatial proximity and bounded neighborhood models, where the crucial distinction is the role of spatial racial spillovers. We operationalize the concept of racial clusters that underlies our empirical approach. The powerful presence of racial clusters, the fact that racial change is concentrated at the boundaries of these clusters, and spatial patterns in Minority shares and housing prices at the boundaries of these clusters all endorse the empirical relevance of these racial spillovers, hence also of the spatial proximity model.

Nearly all existing empirical work in economics is based, however, on the bounded neighborhood model. One can't say *a priori* whether this is crucial in any specific application. We use the insights of our approach to revisit one prominent study, by Card et al. (2008a), that has results apparently at odds with ours. In particular, they consider their results as discrediting the "expanding ghetto model," which is an alternative characterization of the spatial proximity model.

We revisit the Card et al. (2008a) results in two steps. We examine the case of Chicago in 1970-1980, which featured prominently in their discussion. Our re-examination shows that the racial dynamics in their model are highly spatial and strongly consistent with our results emphasizing the role of neighborhood racial spillovers.

We next use insights from the case of Chicago to revisit their all-MSA regressions for 1970-2000 that had seemed to reveal powerful tipping effects. Our results suggest a strong downward revision of the importance of tipping in neighborhood racial change. Their results hold that when a tract is just above a metro-specific tipping point there is on average across decades an 11 percentage point drop in White growth. Importantly, these headline results pool quite distinct social processes in different areas of cities. Our spatially stratified results question this characterization. First, the process in the suburbs is *not tipping*, i.e. Minority entry inducing White exit. Both features are rare in these areas. Instead these areas receive White flight with avoidance of existing Minority areas, what we call *biased White suburbanization*. Second, urban areas less exposed to existing Minority clusters have either zero or small measured tipping. Finally, even in the urban areas more exposed to existing Minority clusters, tipping magnitudes at 5 percentage points on average are less than half of the headline estimates from the prior work. In short, across suburbs, less-exposed, and more-exposed urban areas, tipping is non-existent, tiny, or modest in size. Tipping looms large in narratives of neighborhood racial change, but is of more limited importance in the data.

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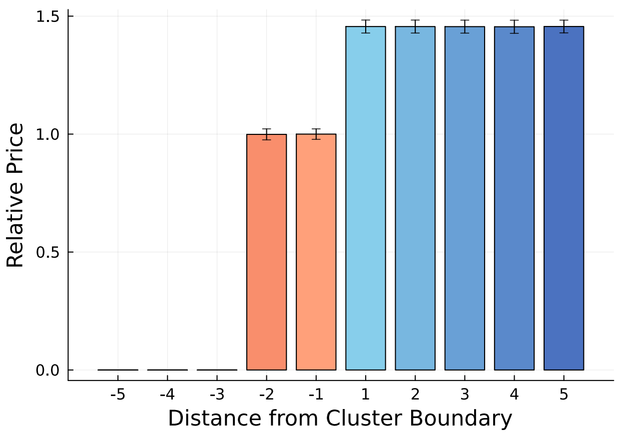
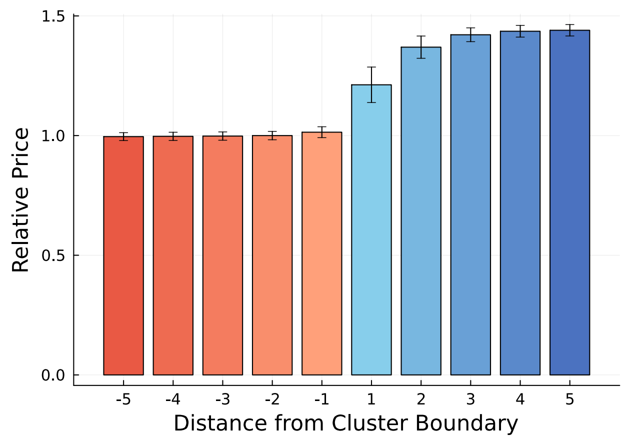
A Additional Figures



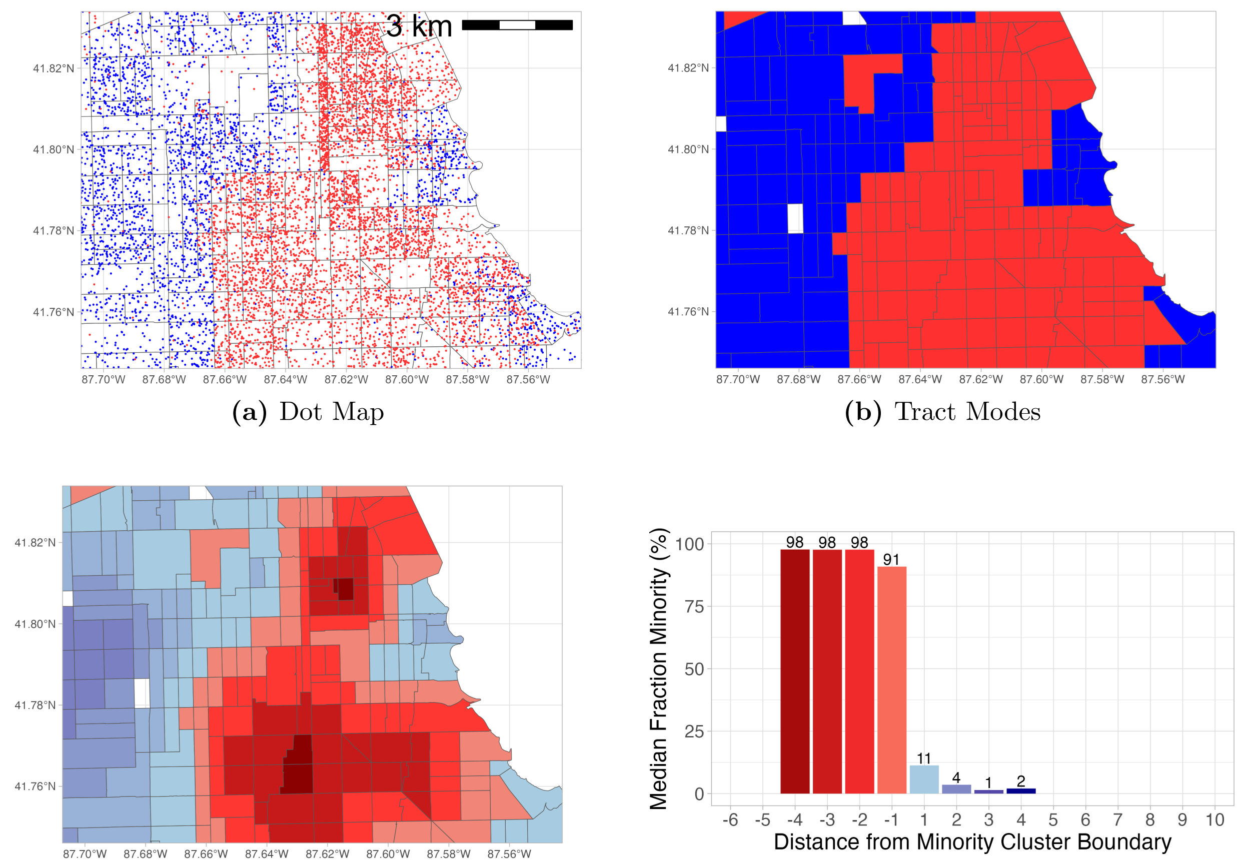
(a) Bounded Neighborhood



(b) Spatial Proximity

Figure A1: Mean Relative Price by Distance from the Cluster Boundary

Notes: Bar plots show averages across 1000 different initializations. Observations with a distance from the cluster boundary larger than 5 are dropped to focus on patterns close to the cluster boundary. Prices are expressed relative to a distance of -2.



(a) Dot Map

(b) Tract Modes

(c) Distance to Cluster Boundary

(d) Histogram by Distance Bin

Figure A2: Construction of Clusters and Distance Bins, South Side of Chicago 1970-1980

Notes: We show how to move from tract population data on race to our representation of minority share by location. Panel (a) illustrates population counts by census tracts; each dot represents 100 individuals, with red dots representing Minorities and blue dots representing Whites. Panel (b) colors census tracts by modal race given the underlying data from panel (a). Panel (c) shades tracts by distance from Minority cluster boundary, with lighter colors indicating closer to a boundary. Panel (d) is a histogram of median fraction Minority by distance bin for all tracts in this sample. Census tract geometries are 2000 geographies; cluster size is set to 1.

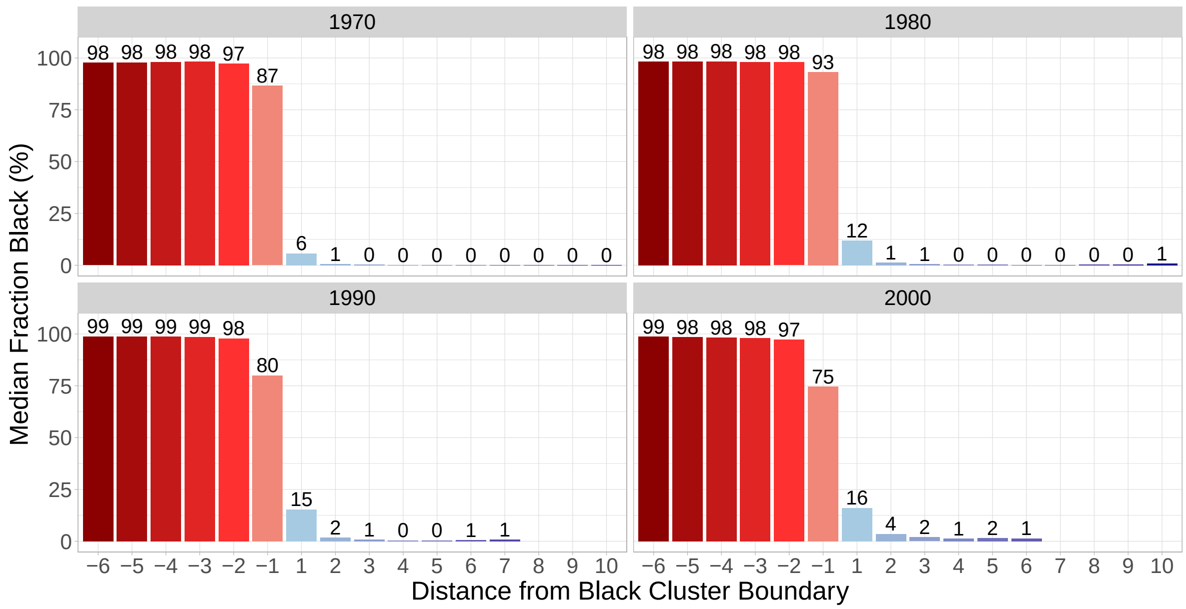


Figure A3: Fraction Black by Distance from Black Cluster Boundary, Chicago MSA, 1970-2000
Notes: Robustness check under alternative racial groups. Gradients are large at the boundary of Black/non-Black clusters in Chicago, though they do smooth out somewhat over time.

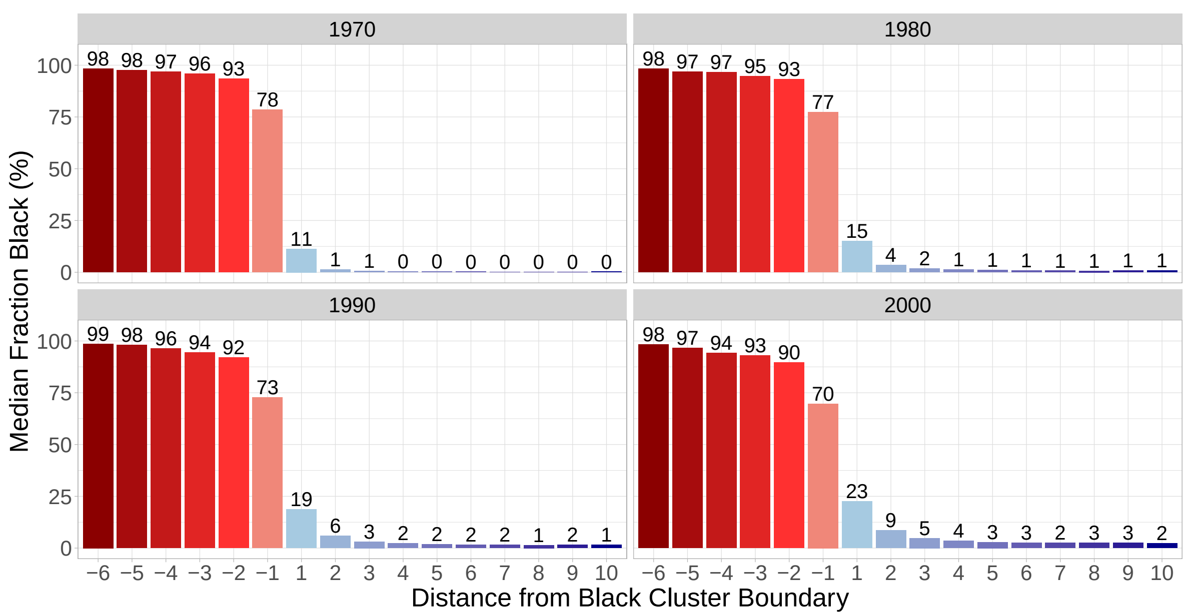
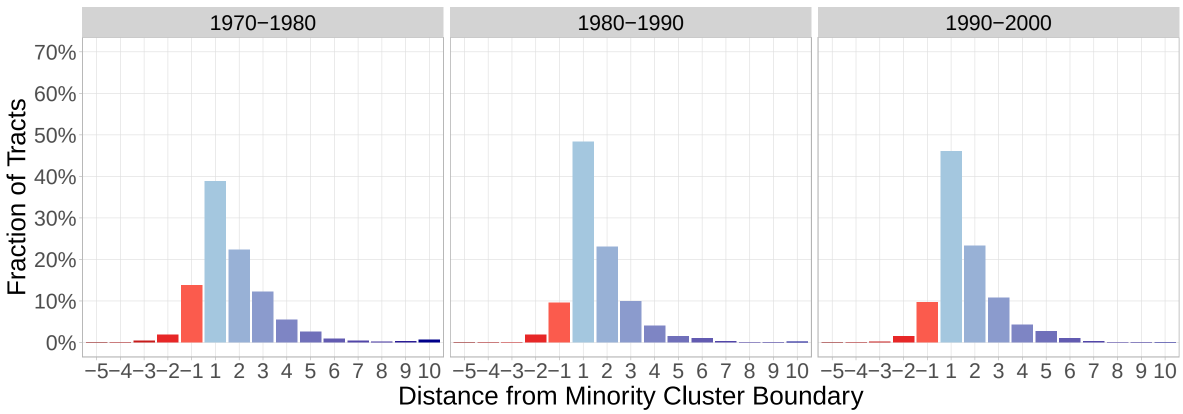
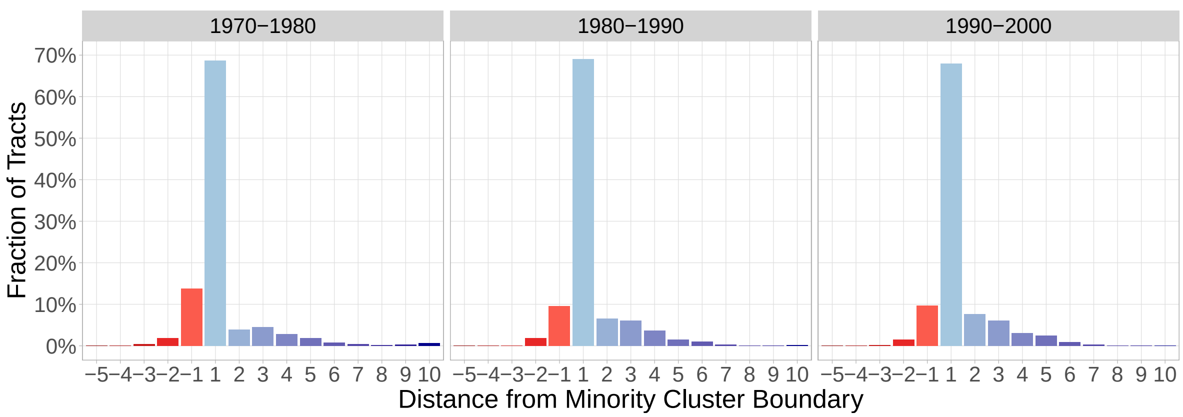


Figure A4: Fraction Black by Distance from Black Cluster Boundary, All MSAs, 1970-2000
Notes: Robustness check under alternative racial groups. Gradients are large at the boundary of Black/non-Black clusters across MSAs, though they do smooth out somewhat over time.



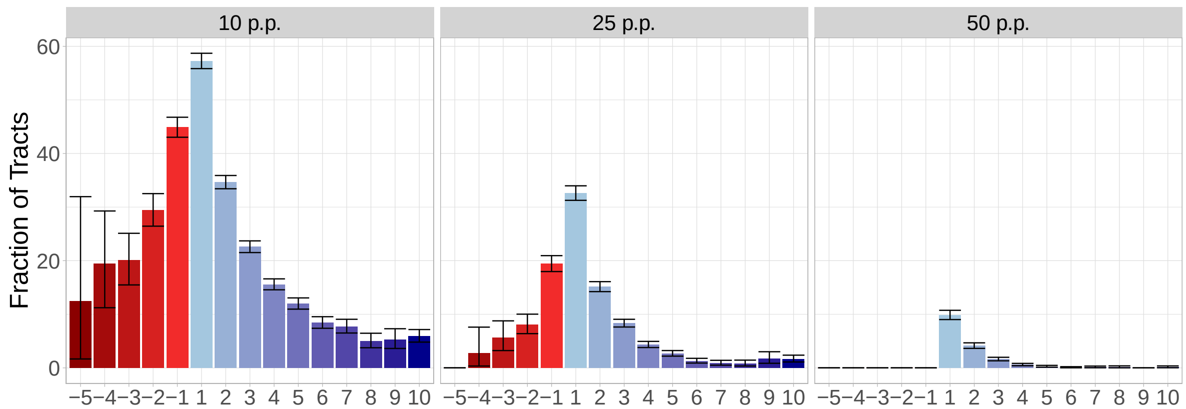
(a) By Location



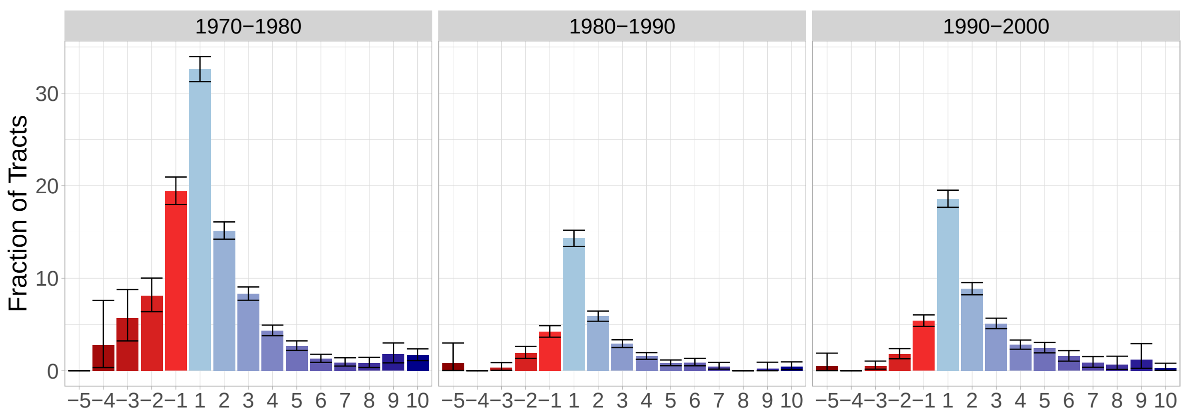
(b) Contiguous Tracts to Boundary

Figure A5: Decline in White Share of 25 p.p. or more, All MSAs 1970-2000

Notes: The locus of racial change occurs predominantly at tracts near and connected to cluster boundaries across decades for all MSAs. In Panel (b), any tracts which experienced 25 p.p. or greater decline in White share and are contiguous with a cluster boundary are put in distance bin 1. Probabilities sum to 100%.



(a) Different Thresholds, 1970



(b) 25 p.p. Change, 1970-2000

Figure A6: Fraction of Tracts with Decline in White Share by Location, All MSAs, 1970-2000

Notes: Racial change occurs predominantly at tracts near to cluster boundaries across decades for all MSAs. 95% confidence bands are provided around each point estimate.

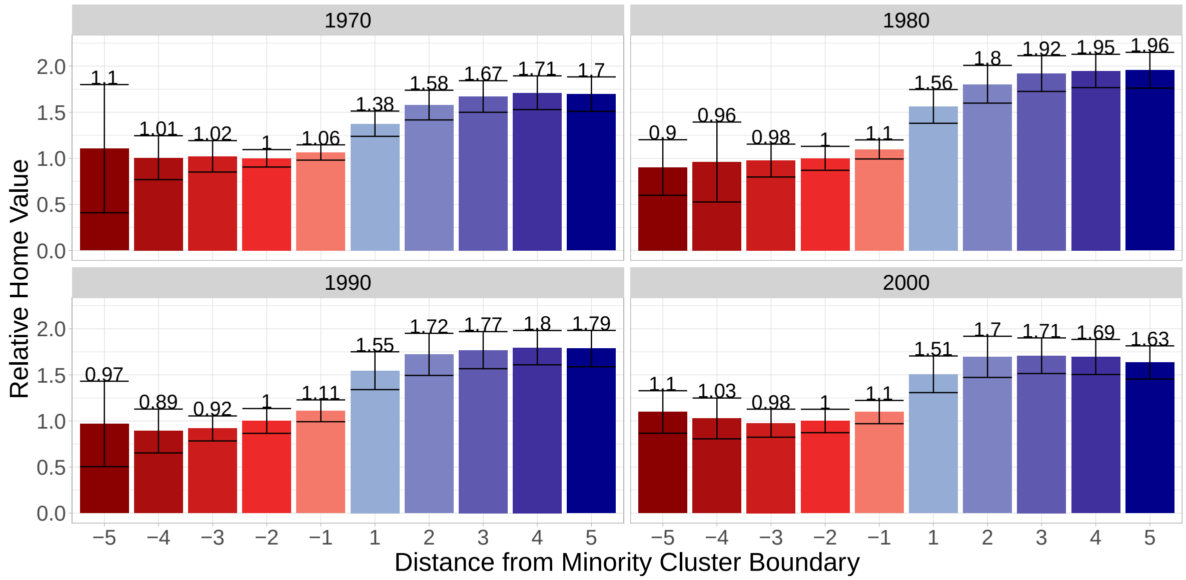


Figure A7: Relative Home Values, All MSAs 1970-2000

Notes: Home values are first normalized by the MSA-specific median home value and then expressed relative to home values at a distance of -2. 95% confidence bands are provided around each point estimate.

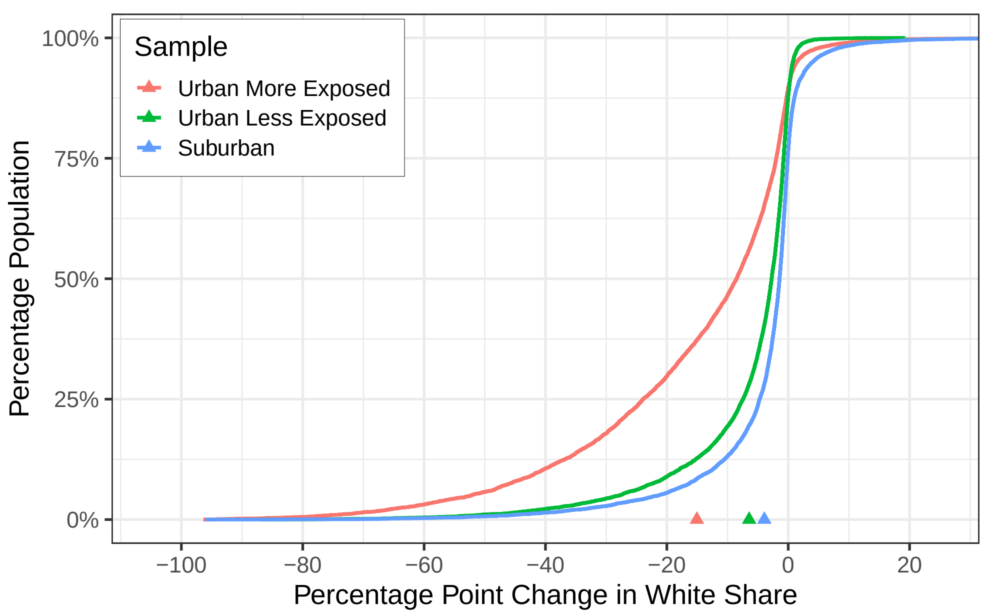


Figure A8: Population Weighted ECDF of Percentage Point Change in White Share, 1970-1980

Notes: 50th percentile changes in White share are noted on the X-axis with the corresponding colored triangle.

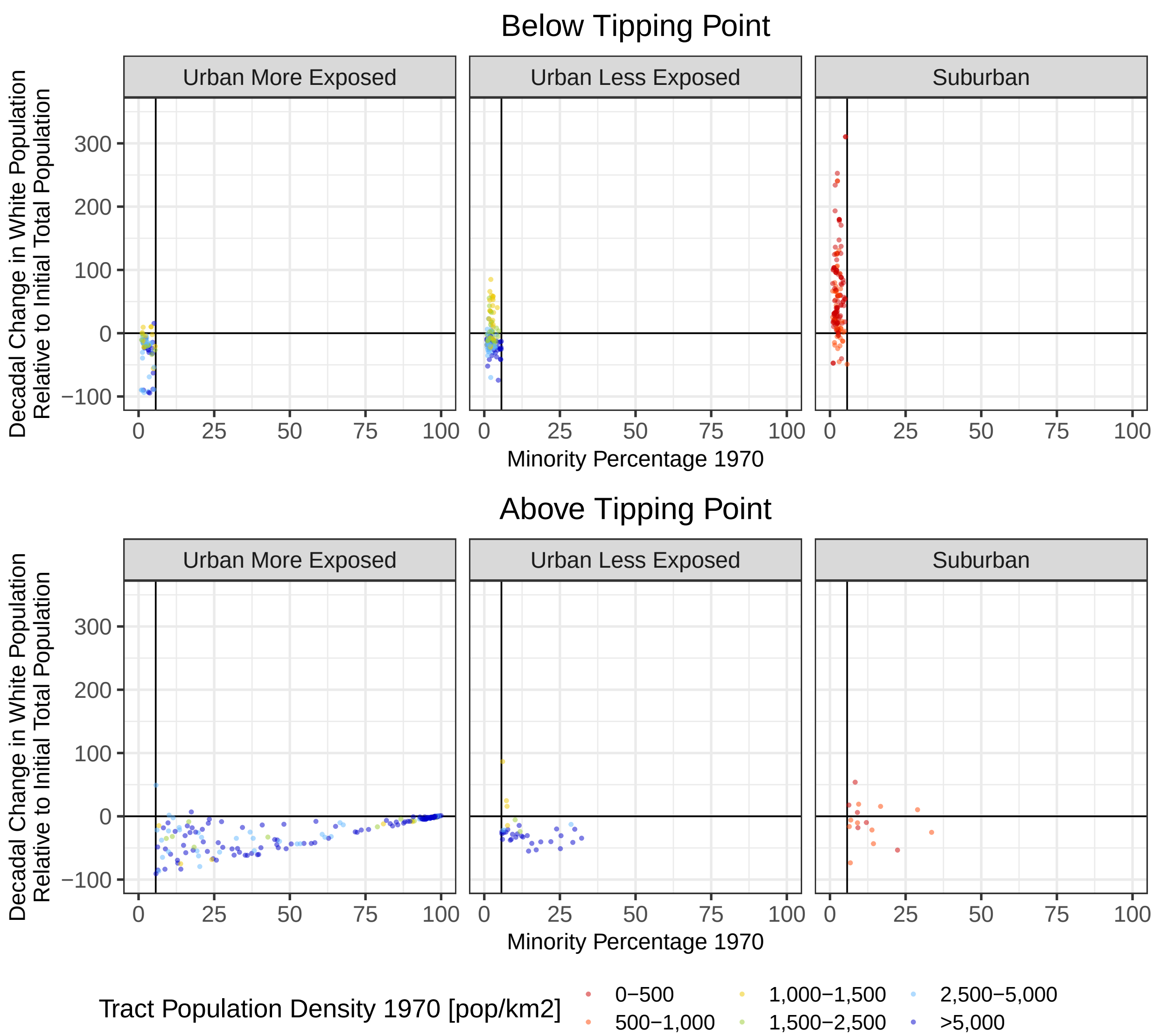


Figure A9: White Population Level Changes by Geographic Split, Chicago 1970-1980
Notes: Colors indicate which quadrant a census tract is located. The split between urban and suburban occurs at population density 1,000. Less exposed urban tracts are those further than distance 2 from a Minority cluster boundary.

B Derivation of bid-rent functions

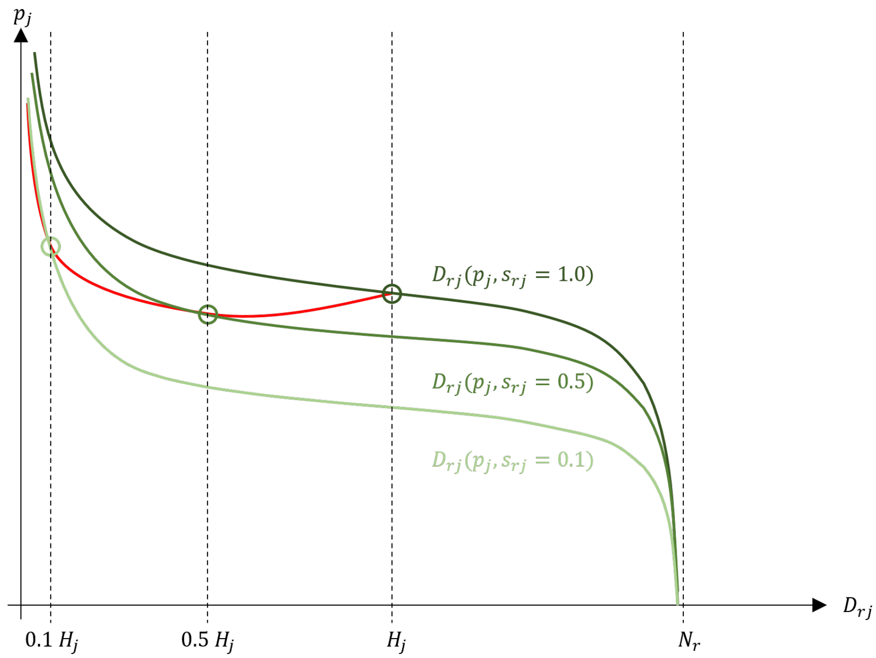


Figure B10: Construction of Bid-Rent Curves from Demand Functions

Notes: Green curves show demand for tract j at different hypothetical Minority shares s_{rj}. Red curve shows the resulting bid-rent function.

A partial equilibrium bid rent-function $b_{rj}(s_{mj})$ describes the maximum willingness to pay of a marginal household of group r to move into location j if the Minority share at that location is s_{mj}. In our setting, it is implicitly defined through the equation

$$D_{rj}(b_{rj}(s_{mj}), s_{mj}; N_r, \eta_{rj}) - H_j s_{rj} = 0,$$

assuming that $\{p_k, s_{mk}, \eta_{rk}\}$ remain unchanged for $j \neq k$. Figure B10 provides graphical intuition for how the bid rent curve is constructed. As both, the White and the Minority bid rent curve depend on s_{mj}, they can be plotted in the same diagram with crossings pinning down (partial) equilibrium Minority shares and neighborhood prices. Stable equilibria are characterized through $b'_{wj} < b'_{mj}$ while intersections where $b'_{wj} > b'_{mj}$ are unstable equilibria.[38] Changes in population sizes N_r or location fundamentals η_{rj} (relative to outside options) can shift the bid-rent curves up and down. If such shifts lead to an intersection where $b'_{wj} = b'_{mj}$ this is a tipping point.

[38] Caetano and Maheshri (2017) refer to such unstable equilibria as tipping points using a closely related "S" shape approach to identify them. We follow the approach of Card et al. (2008a) in what we label a tipping point in partial equilibrium.